Predicting the Price of a Stock

An Interactive Qualifying Project

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WORCESTER POLYTECHNIC INSTITUTE

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Bachelor of Science

by

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Abstract

This project seeks to create a model that can be used to make short-term predictions for the price of stocks. Stock prices depend on many different factors, which cannot all be implemented into a single model. Instead, the model created in this project will primarily rely on the patterns observed in historical stock data. These patterns, when combined with other model improvements, will allow investors to make an educated prediction for the price of a stock in the near future.

Executive Summary

There exists a need for investors to make educated decisions when trading in the stock market. Articles, podcasts, expert forecasts, and advice from friends are often the primary sources of information that new investors use to make their decisions. Mathematical models can also be used to help investors make informed choices with their assets. One benefit to using models is that their historical efficacy can easily be evaluated whereas other sources of information may require more baseless trust.

This project involves the construction and analysis of a prototype model as well as a few refinements that seek to improve upon the prototype model. The prototype model, utilizing linear trends and fourier series, was provided by Professor Humi as the groundwork of the project. This model is the result of previous research conducted by Professor Humi and the students he has advised on this project.

In addition to modeling, this project includes the execution of a research survey designed to analyze college students' investing habits. Fifty WPI students were surveyed in the Ruben Campus Center to get a better understanding of their stock market experience and tendencies. The research concludes that WPI students, by and large, do not attempt to invest in the stock market and would benefit from a mathematical model that they can trust.

In order to gauge the efficacy of the models in this project, several stocks were selected from the healthcare industry to test prediction quality. The historical period of Nov 2018 - Nov 2020 for each stock was used as the data input for the models. The prototype model, which utilizes solely historical stock prices as an input, was able to accurately predict prices up to roughly nine days into the future on average.

To improve upon the prototype model, a moving averages model and a volatility-driven model were created. By smoothing the historical stock data, the moving averages model aims to eliminate noise and better reveal underlying trends. The moving averages model did not demonstrate improvement over the prototype model, however the volatility-driven model was able to accurately predict stock prices up to roughly fourteen days on average, a noticeable improvement over the prototype model.

All modeling in the project was done using MATLAB and was completed from Fall 2020 to Summer 2021. One must consider the impact of the Covid-19 pandemic on the historical stock prices, especially since the stocks analyzed are in the healthcare industry. This project does not constitute professional investing advice. All investments contain risk, and one should not risk money they cannot afford to lose.

Introduction

Investing in the stock market is a very overlooked activity that thousands of young adults never attempt. Many fear the potential of losing large sums of money or believe that investing is too difficult for them to understand. While some people do lose everything in the stock market, there are ways to avoid such risk and have the odds in your favor. For example, the S&P 500, an index of the 500 largest companies in the US stock exchanges, has long-term annualized average returns of 10-20%.

I was inspired to take on this project because I want to develop a tool that myself and others could use to make more calculated investments in the stock market. Oftentimes, new investors will purchase and sell securities based on gut feelings or news articles they read online. The news they have "discovered" is likely already *priced into* the market. This leaves casual investors with few techniques for making educated short-term investments. Developing a new and effective technique has long been an interest of mine.

As a Mechanical Engineering major, it is important to develop methods and then evaluate the effectiveness of those methods. This project is particularly relevant to those skills, as it involves developing, improving, and evaluating a model. In any engineering project, the same steps are taken. Documentation of results and use of statistical analysis are valuable techniques that can be applied to a broad group of studies.

This project will provide me with valuable skills that I can use during the course of my career. Primarily, the ability to use a program like MATLAB is a skill that can be used at any job. It is important to clearly demonstrate, using figures and calculations, the significance of one's findings. The skills used, for both conducting the analysis of this project and creating this report, will be immensely useful in future career roles.

This submission shall qualify as an *Interactive Qualifying Project* (IQP) at Worcester Polytechnic Institute (WPI). WPI defines an IQP as a project that solves a problem "at the intersection of science and society". The stock market is a lively embodiment of our society, as its prices are governed by the Law of Supply and Demand. Any change in the world, good or bad, that impacts people has the ability to impact stock prices. Additionally, many people rely on investing as a means of generating both income and wealth for the future of their family. This project uses mathematical science to hopefully improve the wealth of small investors.

Research

Stock Prices

In order to begin predicting the price of stocks, one must first understand the factors that dictate the price of a stock at any given moment. At the base level, the price of a stock is determined by the supply and demand of that stock in the market. When there are many buyers that want to purchase a stock (high demand), the price of the stock generally increases. On the other hand, when many people are attempting to sell the stock, the price generally decreases. Companies may also adjust the scarcity of a stock by issuing more shares or purchasing back shares. These changes in supply can move the stock price, especially when large quantities of shares are involved.

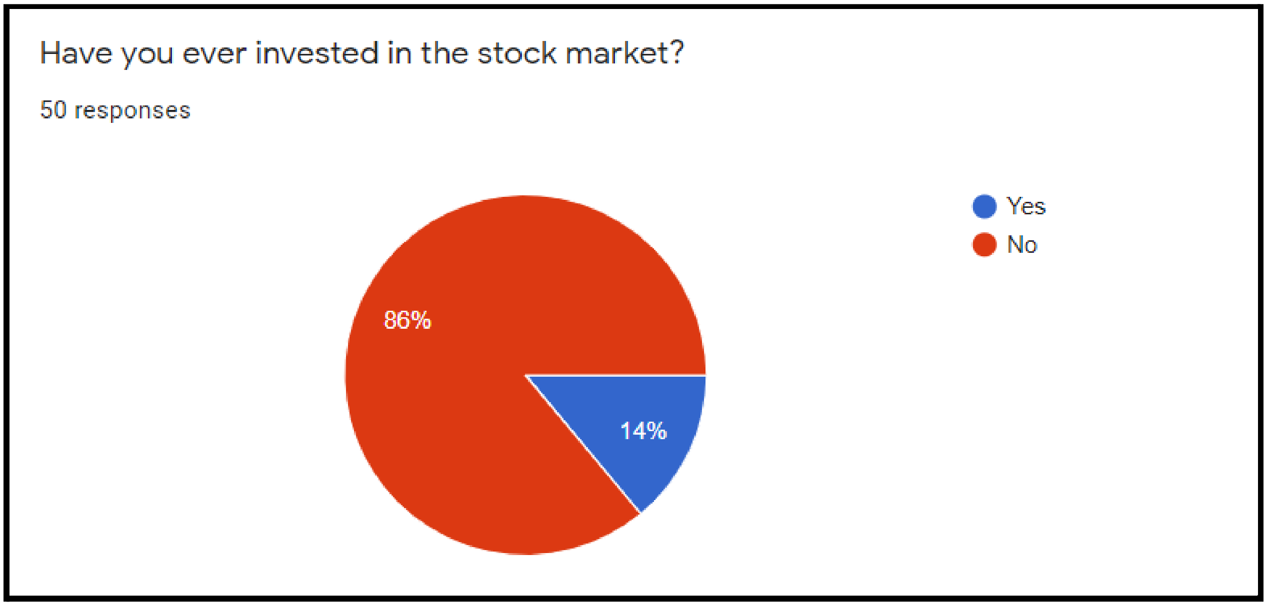
Drivers of Supply and Demand

There are many drivers of supply and demand when it comes to stocks. They might include earnings reports, company news, and orders made by politicians or other wealthy investors. When a company reports its earnings, stock prices are bound to react as investors either gain or lose confidence in the stock due to the company's changes in revenue and costs. Similarly, news articles and press releases can inform investors of reasons to buy or sell their shares. Some investors will try to mimic the moves made by people of status, such as politicians, as these people often have insider information regarding the future price of stocks. The more drivers that can be incorporated into a model, the more accurate predictions it will yield. However, it can be difficult to turn factors such as news articles into numerical values that can be used with a model. Additionally, some events can impact nearly the entire stock market such as the Covid-19 pandemic which caused a crash in March 2020.

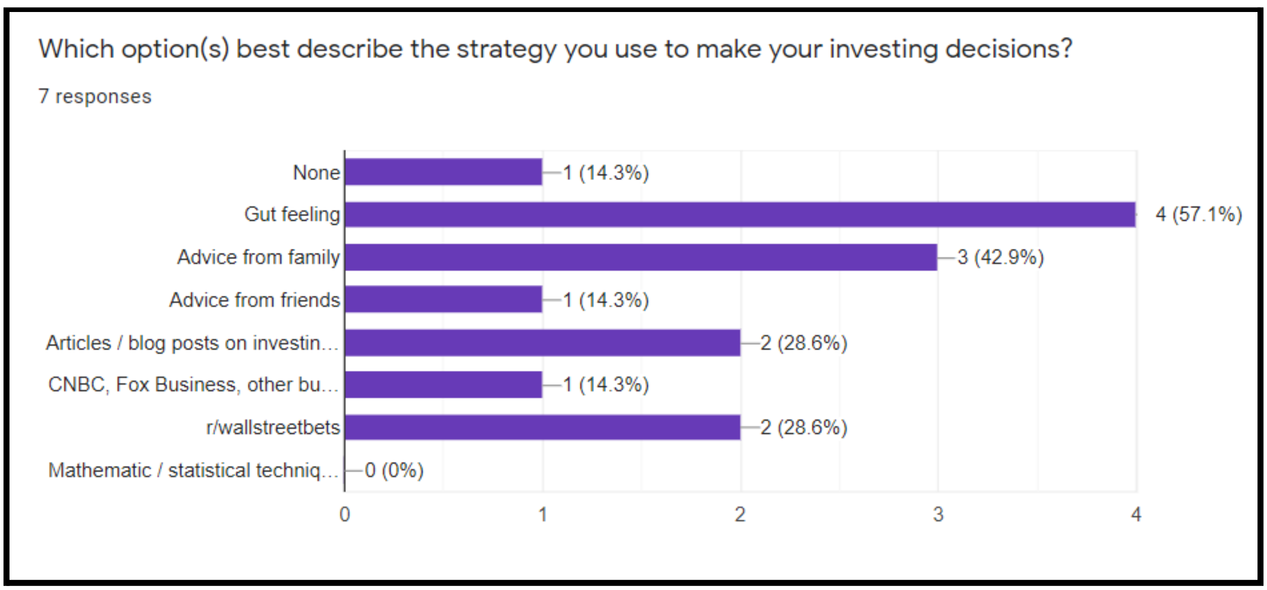
Survey

A survey was constructed in order to better understand the investing habits of college-aged individuals. The aim of the survey was to gauge trading activity, methods, and frequency among the population. Fifty WPI students were selected systematically from the Ruben Campus Center. Each table in the building was approached and asked to participate in a short survey. The process was repeated until fifty responses were collected. The sample is meant to be representative of the entire WPI student body. However, one might make the argument that the subset of students located in the Campus Center may be more social and more inclined to take risks than the average WPI student. This possibility is largely a result of the current Covid-19 pandemic, which has made leaving your dwelling a "risky" endeavor. This possible bias has been noted, although it is not believed to have a large impact on the survey results.

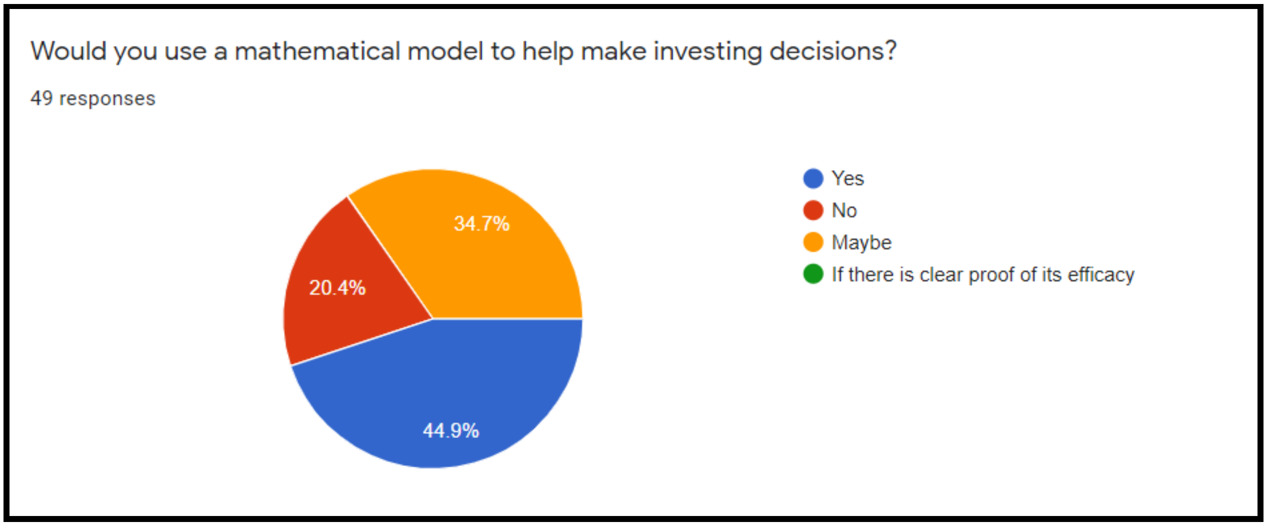
The first result worth noting is that 86% of students surveyed had never done any investing.



Among the 7 students that had invested, none of them had ever used a model to make predictions about the future prices of stocks.



And perhaps most important, a majority of students would be open to considering using a mathematical model to help inform their investing decisions.



There is a clear willingness among students to learn more about the potential advantages of using a model to predict the future price of stocks. However, one would imagine that new investors would want to see proof that a model is reliable before trusting it to advise their transactions.

Creation of Prototype Model

The prototype model for near-future predictions serves as the groundwork for this project. Once the prototype model is created, several doors open regarding minor improvements and additional input factors. For this project, the prototype model was discovered in previous years' work, and the steps for creating it were provided by Professor Humi. However, MATLAB is not a program of intuitive use, so the development of the prototype model proved to be a challenging task, providing important lessons in MATLAB and overall familiarity with the program.

Stocks Selected

The first step in creating the model was selecting stocks to study. The following 16 securities were selected:

- **Johnson & Johnson (JNJ)**

  Johnson & Johnson is a multinational corporation founded in 1866 that engineers consumer health products, medical devices, and pharmaceuticals. It owns several household brands such as Tylenol, Motrin, and Zyrtec as well as many surgical devices and standard hospital equipment. It is one of the most prominent companies in the sector, which is why the value of its stock is expected to grow.

- **Gilead (GILD)**

  Gilead Sciences is an American pharmaceuticals company that focuses on antiviral drugs. Additionally, Gilead has become involved in Coronavirus treatments, including the drug Vekruly and antiviral "cocktails". The company is a giant that employs 11,800 people, so it should be relatively stable in years to come.

- **Becton Dickinson (BDX)**

  BD is multinational medical device company that produces equipment and disposable devices for hospitals and clinics. BD recently acquired Bard Medical. BD's lineup includes a plethora of devices found in hospitals, and BD continues to have very large contracts with hospitals and clinics around the world. Overall, there are positive prospects.

- **Medtronic (MDT)**

  Medtronic, headquartered in Ireland for tax purposes, is an American medical device company that produces instruments for a large variety of health needs, including surgery. Medtronic devices are commonly found in hospitals and clinics. Medtronic is a growing company with positive prospects that may one day have the name recognition of companies like JNJ.

- **Hologic (HOLX)**

  Hologic is a medical device company focused on Women's Health. Headquartered in Massachusetts, it is at the forefront of engineering Breast Cancer and GYN health devices. Hologic acquired Cynosure and then sold it shortly afterwards, netting a substantial loss.

- **Boston Scientific (BSX)**

  Boston Scientific is a medical device company that focuses on instruments for interventional procedures. The company is best known for its stent, a device used to open blood flow in failing arteries. Boston Scientific is seeing steady increases in its financial metrics and is outperforming smaller interventional device companies.

- **ICU Medical (ICUI)**

  ICU Medical is a California-based medical device company that specializes in vascular therapy, oncology, and critical care applications. ICU's technology is designed to prevent bloodstream infections. This is accomplished through their advanced IV therapy products.

- **Fresenius Medical Care (FMS)**

  Fresenius Medical Care is the leader in the world of Kidney Dialysis. Their Dialysis devices are found in hospitals across the country. Prospects for Fesenius are quite good, as kidney dialysis remains to be a much needed treatment.

- **Abbott Laboratories (ABT)**

  Abbott Laboratories is an American medical supplement company. Its products include baby formula and mineral-rich supplements to aid in preventing dehydration. It is perhaps best known for its nutritional aid Pedialyte, among other products. Abbott also has an extensive device lineup, with many cardiovascular products. ABT is a S&P 100 component.

- **Cardinal Health (CAH)**

  Cardinal Health, a medical solutions company, is the 14th largest revenue generating company in the USA. Its products are found in 90% of hospitals in the country. Cardinal Health is a S&P 500 component that has made several acquisitions over the years. Its main function is production and distribution of medical devices and equipment. CAH has a positive outlook.

- **Stryker (SYK)**

  Stryker is a medical technology company based in Michigan. Its products include hospital beds, surgical instruments, and other specialty devices. Stryker's joint replacement technology is at the forefront of the market. The company is a S&P 500 component.

- **Edwards Lifescience (EW)**

  Edwards, based in California, specializes in artificial heart valves. It also designs devices related to other cardiac functions. Edwards acquired CAS Medical Systems in 2019 and continues to specialize in heart valves. The company is a S&P 500 component.

- **Varian Medical Systems (VAR)**

  Varian specializes in cancer treatments through radiation. Its products include software and hardware-related devices. Cancer detection, through high end x-ray and scanning devices is one of Varian's main specialties. A leader in radiotherapy, Varian has strong potential to continue growth.

- **Danaher (DHR)**

  Danaher is an American conglomerate that holds many medical science and industrial companies. It mainly focuses on environmental quality and general life sciences. Danaher also has some diagnostics divisions. It is a S&P 100 component.

The stocks were selected for a number of reasons. Firstly, they are securities in the healthcare industry. Studying the market in one particular industry narrows down the amount of variables that could potentially disrupt the accuracy of models created. The stocks are also priced between roughly \$20 - \$250 per share. Selecting stocks with similar prices may also improve the chances of creating an accurate model of their behavior. Lastly, these stocks were selected as their historical prices seem to reflect market factors rather than displaying massive volatility from unpredictable events.

For creating the prototype model, 502 days of historical closing prices were downloaded from Yahoo Finance and saved as a CSV file for each stock. Two years of data was deemed a sufficient quantity to create a model.

Autocorrelation

The first step towards creation of the prototype model is *autocorrelation.* The autocorrelation function (ACF) is used to measure the similarity of data points over time. Starting with the most recent point, the function examines the correlation of the point with the point before it, continuing to add one point at a time. As the lag (the number of points from the most recent one) increases, the autocorrelation usually decreases in value.

$$r_k = \frac{\sum_{i=1}^{N-k}(Y_i - \bar{Y})(Y_{i+k} - \bar{Y})}{\sum_{i=1}^{N}(Y_i - \bar{Y})^2}$$

Figure 1: The autocorrelation function

The ACF is used in the prototype model to determine a relevant period, the number of days into the past that each stock's closing prices demonstrates a non-zero correlation.

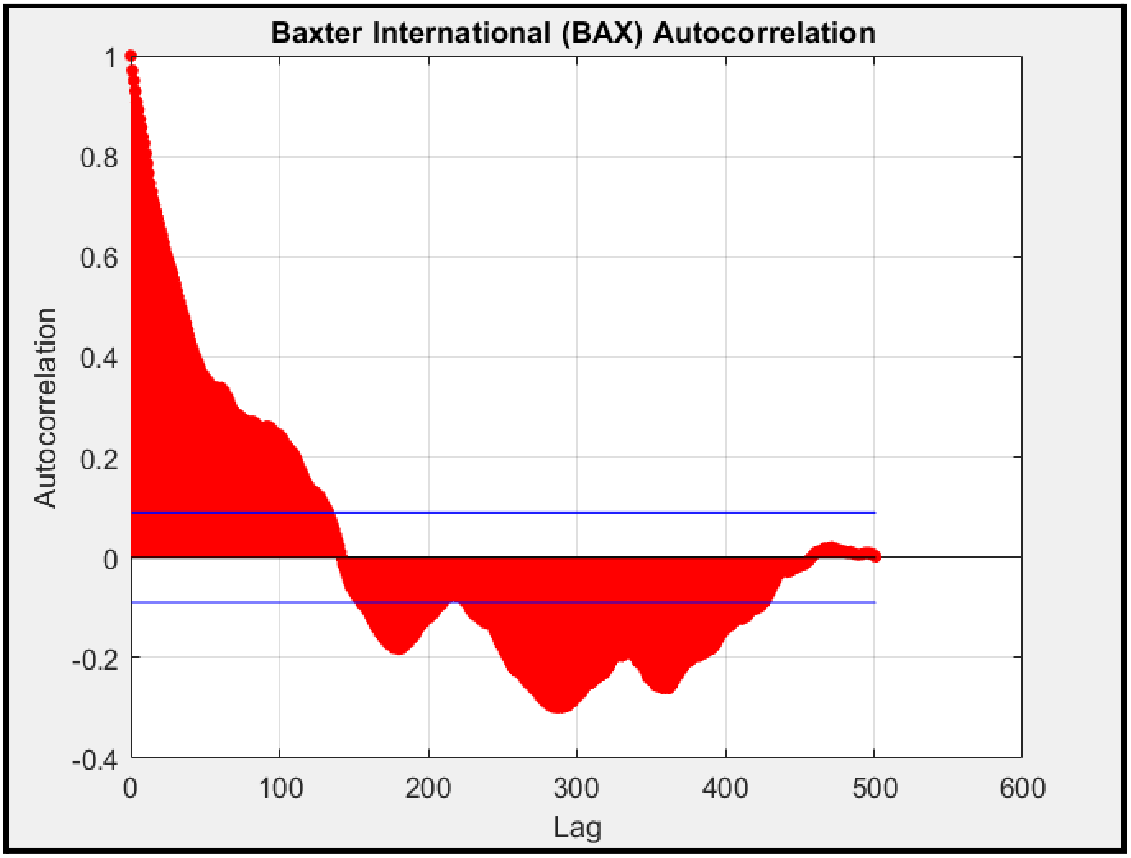


Figure 2: Autocorrelation on BAX

The ACF performed above reveals a relevant period of 143 days into the past (x-intercept). This relevant period will become the subset of data used for the rest of the prototype model steps. The reason for this being that the prototype model seeks to utilize the direction in which the price is currently trending.

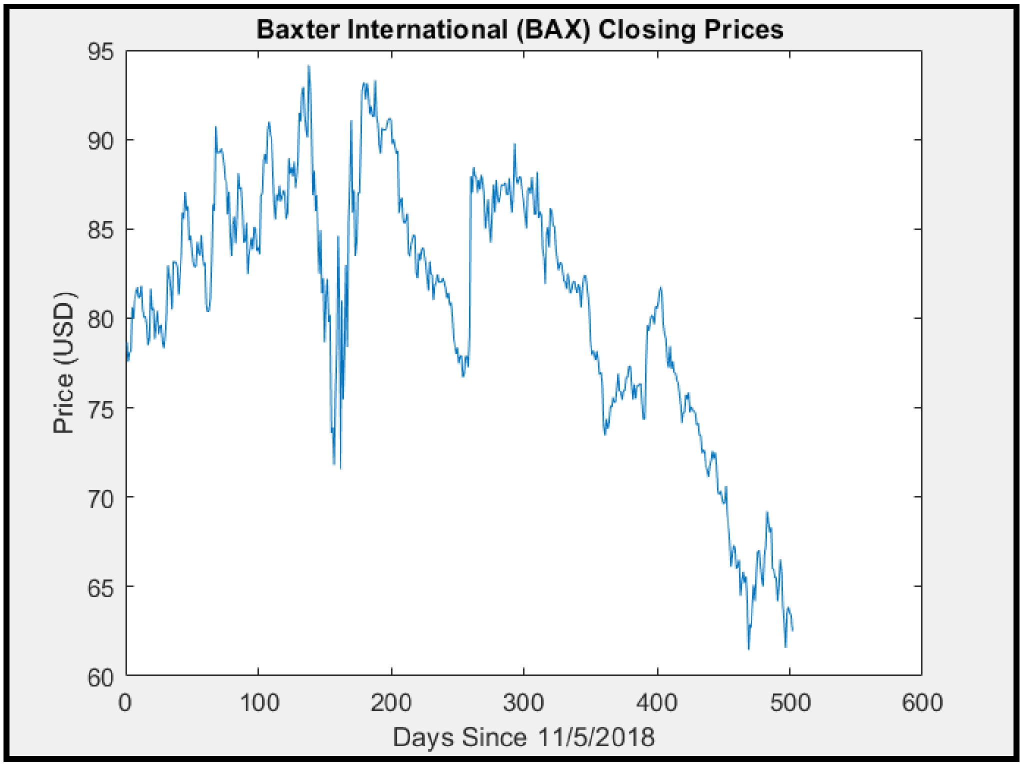


Figure 3: BAX closing prices

The findings of the ACF can be visually confirmed using the graph of closing prices. A substantial correlation can be seen 143 days into the past on the graph above (starting at x=500 and looking left).

Linear Trendline

With the relevant period of each stock determined, the next element of the prototype model is a simple linear trendline. The regression equation, y = a + bx, for the trendline is found using the following formulas.

$$a = \frac{(\Sigma y)(\Sigma x^2) - (\Sigma x)(\Sigma xy)}{n(\Sigma x^2) - (\Sigma x)^2}$$

$$b = \frac{n(\Sigma xy) - (\Sigma x)(\Sigma y)}{n(\Sigma x^2) - (\Sigma x)^2}$$

Figure 4: Coefficients of linear regression

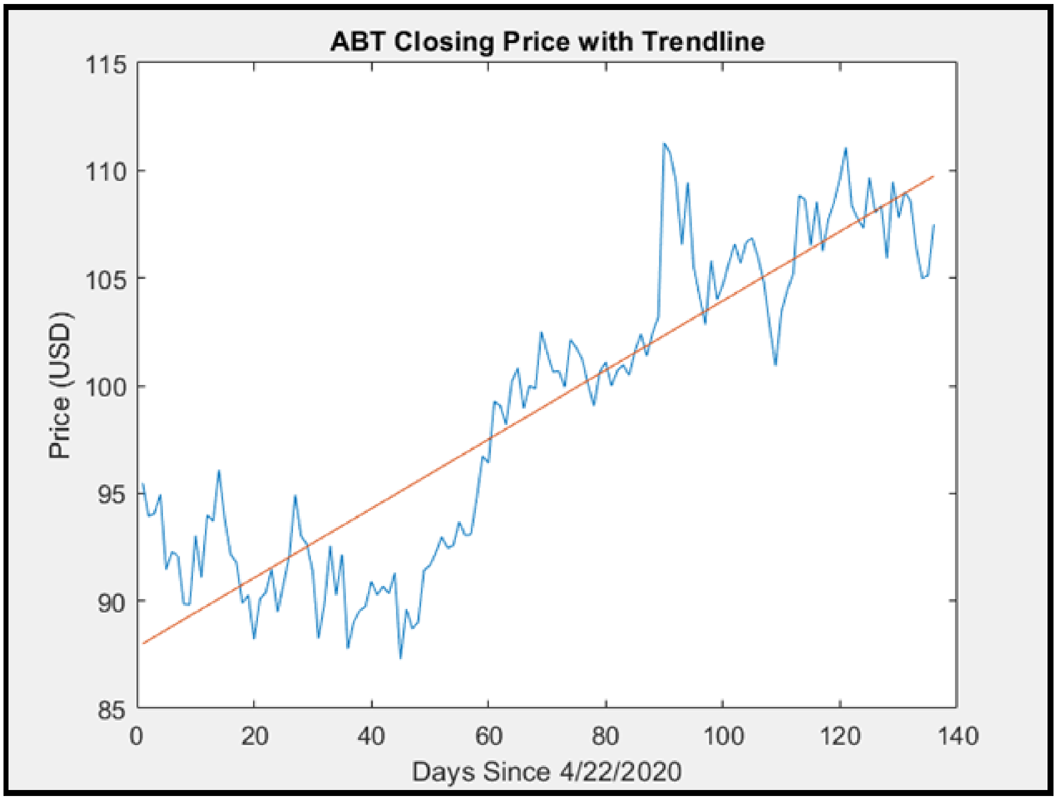


Figure 5: Relevant period of ABT with linear regression

The linear regression composes half of the prototype model. The next element of the prototype model is creating a model of the residuals from the linear regression. As seen above, the residuals appear to oscillate above and below the trendline.

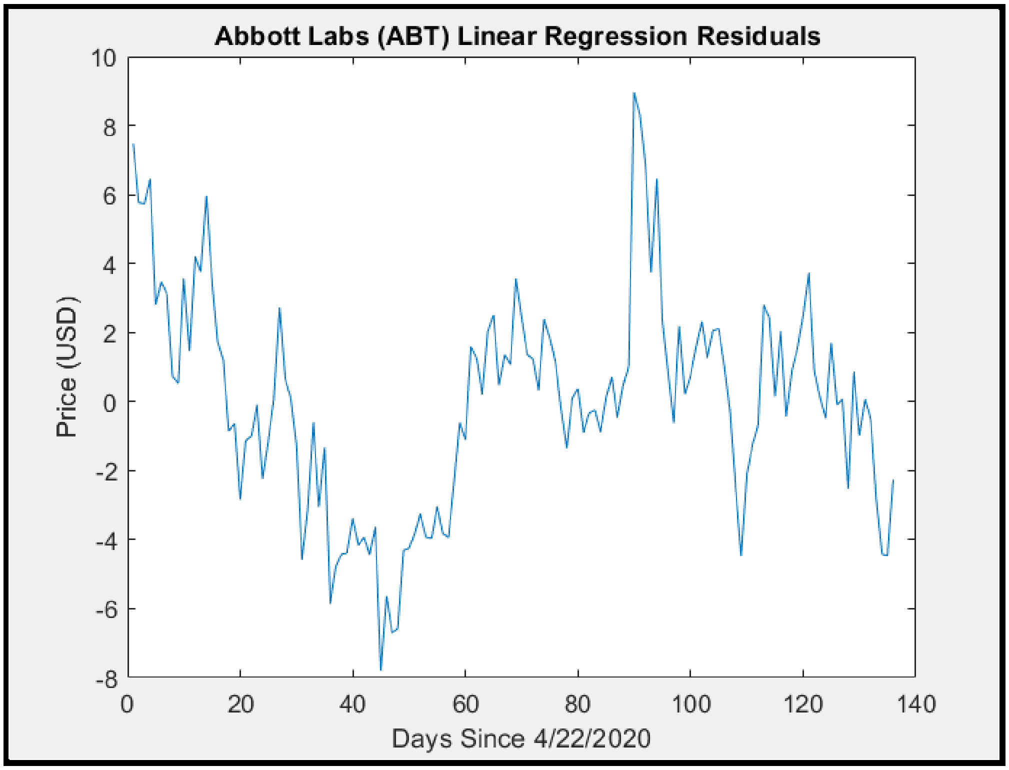


Figure 6: The residuals from Figure 4

<u>Fourier Series</u>

Fourier Series are used in the prototype model to model the residuals from linear regression, such as the residuals shown above. A Fourier series is a periodic function that combines sine and cosine waves in a process known as weighted summation. Fourier series are mainly used for signal processing (such as with sound or electromagnetic waves) and approximation, the latter of which will be utilized extensively in the model. The basic composition of a Fourier series is shown below, where a_0, a_n,and b_n are coefficients derived from the integrals displayed in Figure 7.

$$\boxed{f(x) = \frac{1}{2} a_0 + \sum_{n=1}^{\infty} a_n \cos(nx) + \sum_{n=1}^{\infty} b_n \sin(nx),}$$

Figure 7: Fourier Series

$$a_0 = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x)\, dx$$
$$a_n = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \cos(nx)\, dx$$
$$b_n = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \sin(nx)\, dx$$

Figure 8: Fourier Coefficients

Applying a three-term Fourier series to the residuals and adding the series to the linear regress of the relevant period yields the prototype model.

<u>Complete Prototype Model</u>

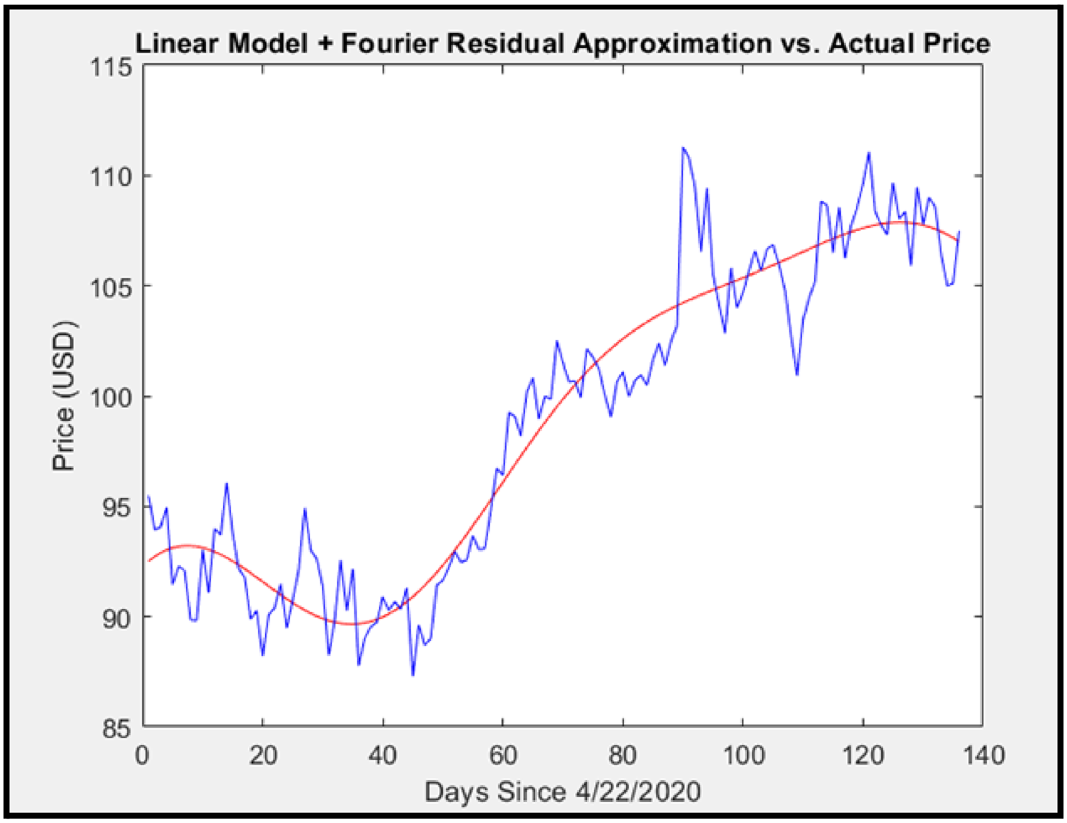


Figure 9: The prototype model for the relevant period of ABT

In order to use the prototype model to make predictions, a noise band around the model was created to reflect the maximum and minimum residuals obtained from the data used to create the model.

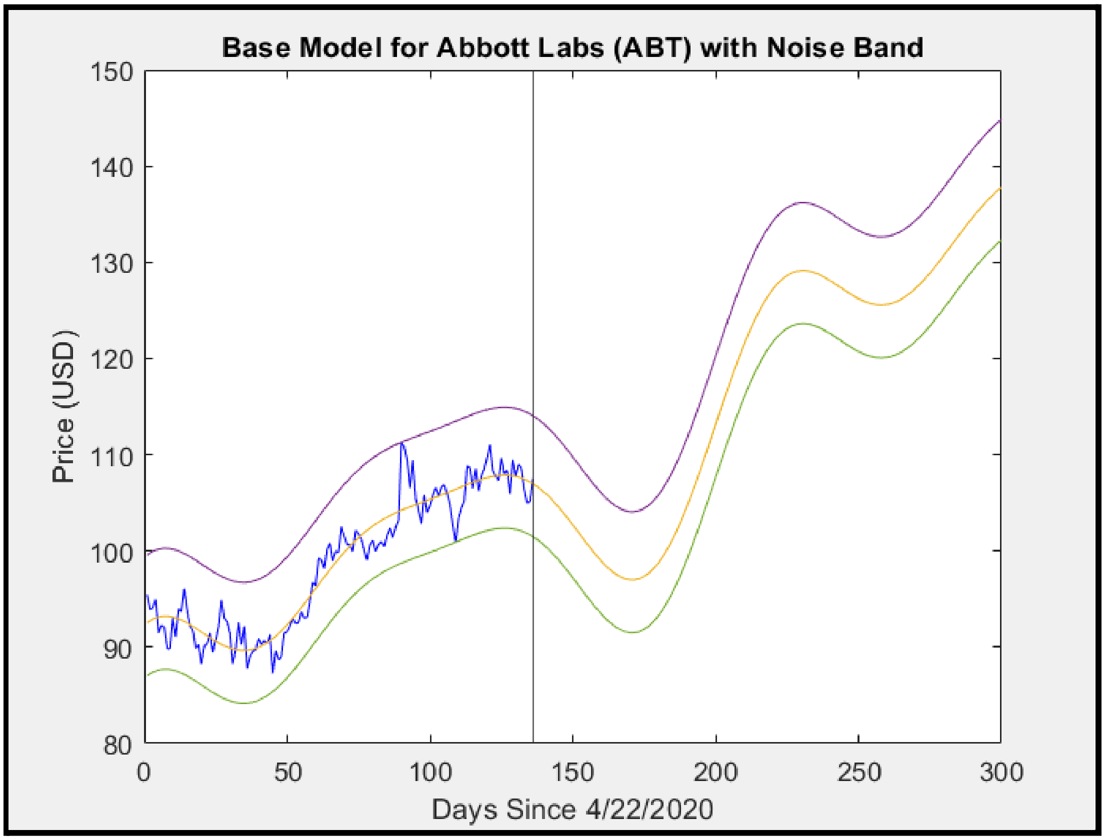


Figure 10: Base model for ABT with Noise Band

Accuracy of the Prototype Model

In order to determine the accuracy of the prototype model, future stock data was compared to the model and the number of days that the future data remained in the noise band was noted. The model, on average, was able to provide a reasonable prediction for up to 9 days into the future.

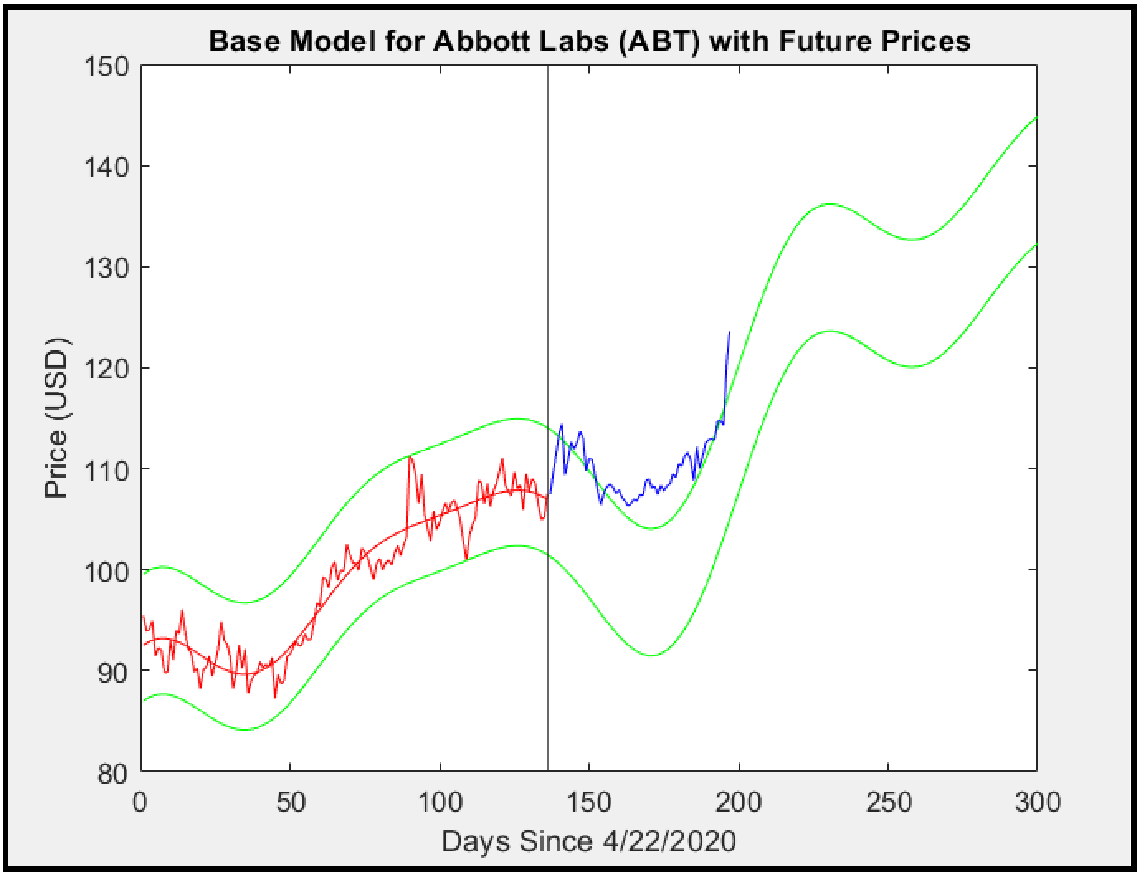


Figure 11: The future prices for ABT remain within the noise band for 4 days.

The vertical line in Figure 8 indicates the point at which the stock prices switch from historical to future. The historical prices were used to create the prototype model. The future prices are independent from the model and are the prices which the model seeks to accurately predict.

Model	Days In Band
ABT1	4
BAX1	16
BDX1	3
BSX1	6
CAH1	1
DHR1	6
EW1	6
FMS1	4
GILD1	3
HOLX1	6
ICUI1	10
JNJ1	56
MDT1	6
SYK1	6
VAR1	4
ZBH1	6
mean	8.94
median	6
standard deviation	12.58

Table 1: Prediction quality of prototype model

The prototype model, as expected, was unable to predict very far into the future. In order to improve the accuracy of predictions, several measures were considered. The hypothesis was that market indices, such as the NASDAQ Composite, could be utilized. One way of doing so would be to project the index into the future, using the same method as the prototype model, and then use that projection to influence the projection of an individual stock. The influence could be weighted by considering the correlation coefficient of the stock's closing prices and the index's closing prices.

Creation of the Moving Average Model

In order to improve upon the prototype model, the implementation of moving averages was considered. The moving average technique smooths the stock data in an attempt to better represent price trends by minimizing the impact of the inexplicable "noise" in the data. The moving average function works by replacing the raw data points with the corresponding average value of 10 days before and after said data points.

```
[n,m]=size(ABT(:,5))
tend=n
for i=10:tend-10
az=0;
for j=1:20
az=az+prclose(i+j-10);
end
prsmooth(i)=az/20;
end
```

Table 2: Moving average technique in MATLAB

Table 2 displays the moving average portion of the MATLAB script for the moving average model. The closing price data points are smoothed using the average value of a 20-day window centered on each point. The smoothing is not applied to the first and last 10 data points because it is not possible to fit a 20-day window around them.

With the data smoothed, the moving average model is then created in the same manner as the prototype model. The aim of the smoothing being to negate the effects of minor fluctuations in the stock price in order to better represent the underlying trends.

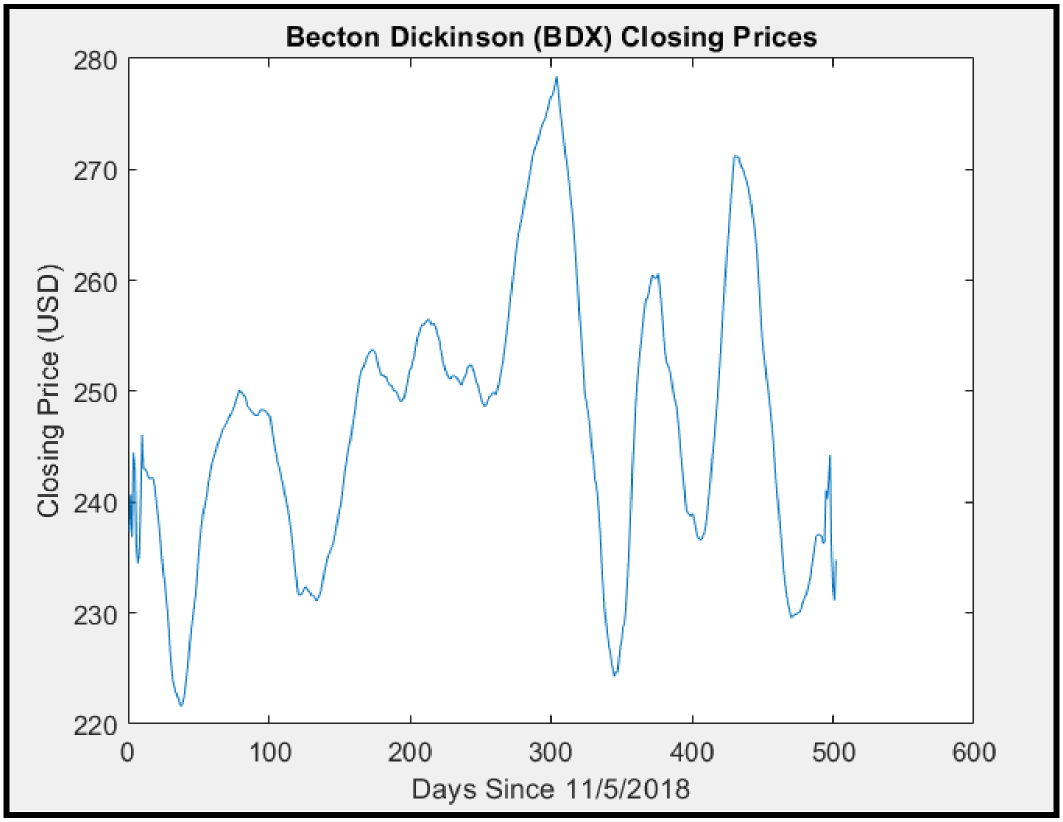


Figure 12: The BD Closing Prices after smoothing

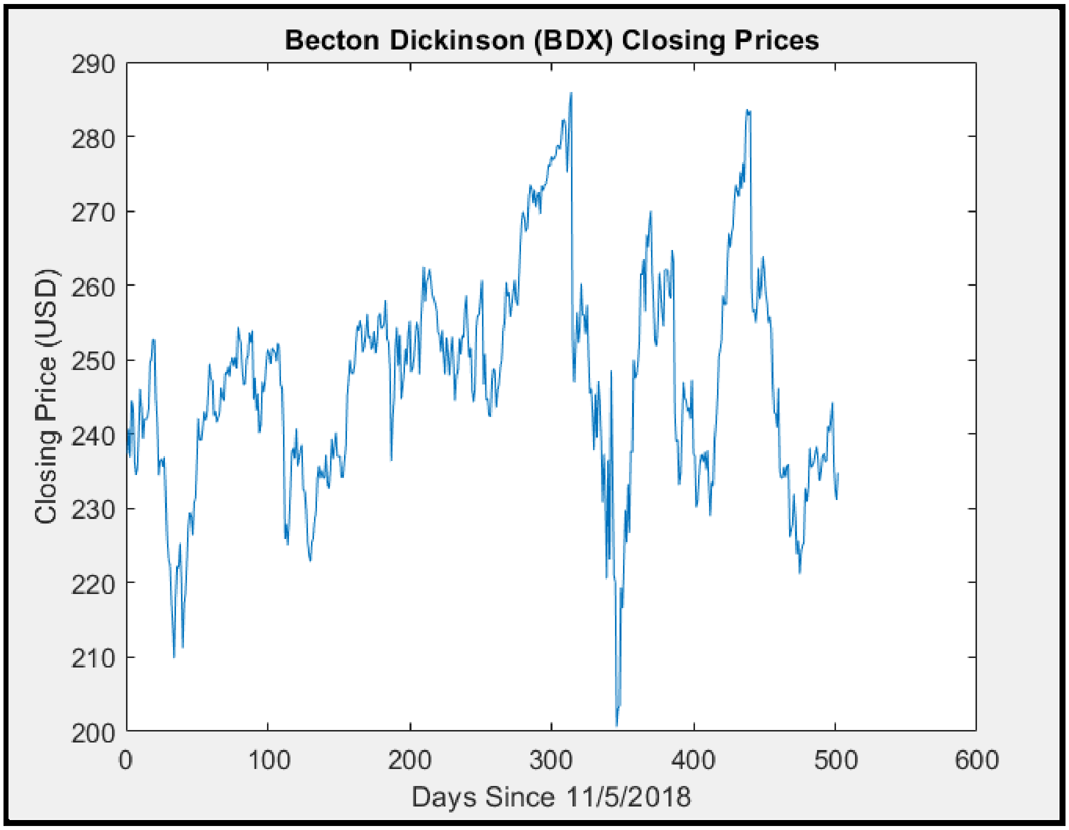


Figure 13: The BD Closing Prices before smoothing

Accuracy of the Moving Average Model

In order to determine the accuracy of the moving averages model, future stock data was compared to the model and the number of days that the future data remained in the noise band was noted. The model, on average, was able to provide a reasonable prediction for up to 4 days into the future.

Model	Days In Band
ABT2	3
BAX2	3
BDX2	4
BSX2	1
CAH2	1
DHR2	6
EW2	5
FMS2	2
GILD2	2
HOLX2	4
ICUI2	4
JNJ2	16
MDT2	6
SYK2	5
VAR2	3
ZBH2	1
mean	4.13
median	3.5
std deviation	3.46

Table 3: Prediction quality of moving average models

Unfortunately the moving average model did not improve upon the prototype model. This would appear to indicate that the prediction error associated with the prototype model is not a direct result of the noises in the price trends.

Creation of the Volatility-Driven Model

The volatility of a stock is a good indicator of how drastically one can expect the stock's price to change over a period of time. Volatile stocks are known for their prices undergoing significant changes in short amounts of time, while stocks that are not volatile tend to behave more predictably and have less noise in the data.

One measure of volatility is standard deviation. The standard deviation of a stock's historical closing prices is calculated as follows.

$$\sigma = \sqrt{\frac{\sum (x_i - \mu)^2}{N}}$$

σ = population standard deviation

N = the size of the population

x_i = each value from the population

μ = the population mean

Figure 14: Standard deviation formula

Stocks whose closing prices have a higher standard deviation over a historical period are considered more volatile. In order to incorporate standard deviation into the model, it was decided that the historical volatility of the stock should be used to adjust the impact of the fourier series from the prototype model. Stocks with higher volatility, and therefore more noise, may be better modeled by a fourier series as the fourier series is the modeling element that attempts to model the unexplained variation in the stock prices. The linear trendline will still be the backbone of the model; it is simply the fourier series that is adjusted.

On the other hand, stocks with low volatility are likely best modeled by the linear trendline as one does not expect them to behave as erratically. Therefore, each stock's standard deviation was converted to a relative volatility coefficient that was multiplied by the fourier series from the prototype model. Relatively volatile stocks would have a coefficient greater than one, increasing the effect of the fourier series, while relatively stable stocks would have a coefficient greater than zero and less than one, diminishing the effect of the fourier series.

The relative volatility coefficient for each stock was calculated by first finding the standard deviation of each stock's historical closing prices and then calculating a mean standard deviation for all sixteen stocks. Each standard deviation was then divided by the mean standard deviation, yielding the relative volatility coefficient (RVC).

$RVC_{stock} = \sigma_{stock} / \mu_{SD\ of\ all\ Stocks}$

Stock	Standard Deviation	Relative Volatility Coefficient (SD / mean SD)
abt	10.5415	0.847608475
bax	7.2516	0.583078084
bdx	14.6929	1.181409341
bsx	3.4447	0.276977367
cah	4.0798	0.328043737
dhr	32.3971	2.604947733
ew	9.8207	0.78965124
fms	3.4974	0.281214806
gild	4.872	0.391742019
holx	8.0968	0.651037926
icui	29.5052	2.372419255
jnj	7.818	0.628620505
mdt	9.4647	0.761026413
syk	18.9422	1.523082034
var	19.4112	1.560792831
zbh	15.1523	1.218348233
mean	12.43675625	

Table 4: Calculating relative volatility coefficients

```
for x=1:300
prd(x)=p(1)*x+p(2)+0.847608475*f(x);%relative volatility coefficent%
end
```

Table 5: A relative volatility coefficient multiplied by the fourier series in MATLAB

Accuracy of the Volatility-Driven Model

In order to determine the accuracy of the volatility-driven model, future stock data was compared to the model and the number of days that the future data remained in the noise band was noted. The model, on average, was able to provide a reasonable prediction for up to 14 days into the future. This was a noticeable improvement upon the prototype model.

Model	Days In Band
ABT3	5
BAX3	48
BDX3	4
BSX3	44
CAH3	3
DHR3	6
EW3	6
FMS3	7
GILD3	7
HOLX3	6
ICUI3	7
JNJ3	56
MDT3	6
SYK3	6
VAR3	5
ZBH3	6
mean	13.88
median	6
stdev	17.20

Table 6: Prediction quality of the volatility-driven model

It appears that by adjusting the influence of the fourier series, the model was able to make better predictions for most stocks.

Conclusion

Predicting the price of stocks is not easy. If there was a sure way to do it, investing would change drastically and everybody would partake. While many good modeling methods have been invented in the decades since the required technology became available, nobody has come close to fully “cracking the code”. Models for stock prices are limited by the number of inputs they have. In the case of this project, the models were limited to only making predictions based on historical stock data. Other sources of information have the potential to improve the model predictions, however some are easier to incorporate than others. For example, one can factor in trends in market indices, but it would be much harder to factor in something like comments from a popular investing talk show.

This project aimed to create and improve upon a model that can make short-term predictions for the future price of stocks. The models were able to do so, but one must consider the substantial margin of error that is the noise band. The model is not believed to be a standalone source of investing information, but it may be paired with other sources to aid short-term decision making.

The real success in this project would be the wealth of knowledge it has generated in the area of MATLAB programming and general modeling techniques. These skills are very useful and will surely be of benefit in the future.

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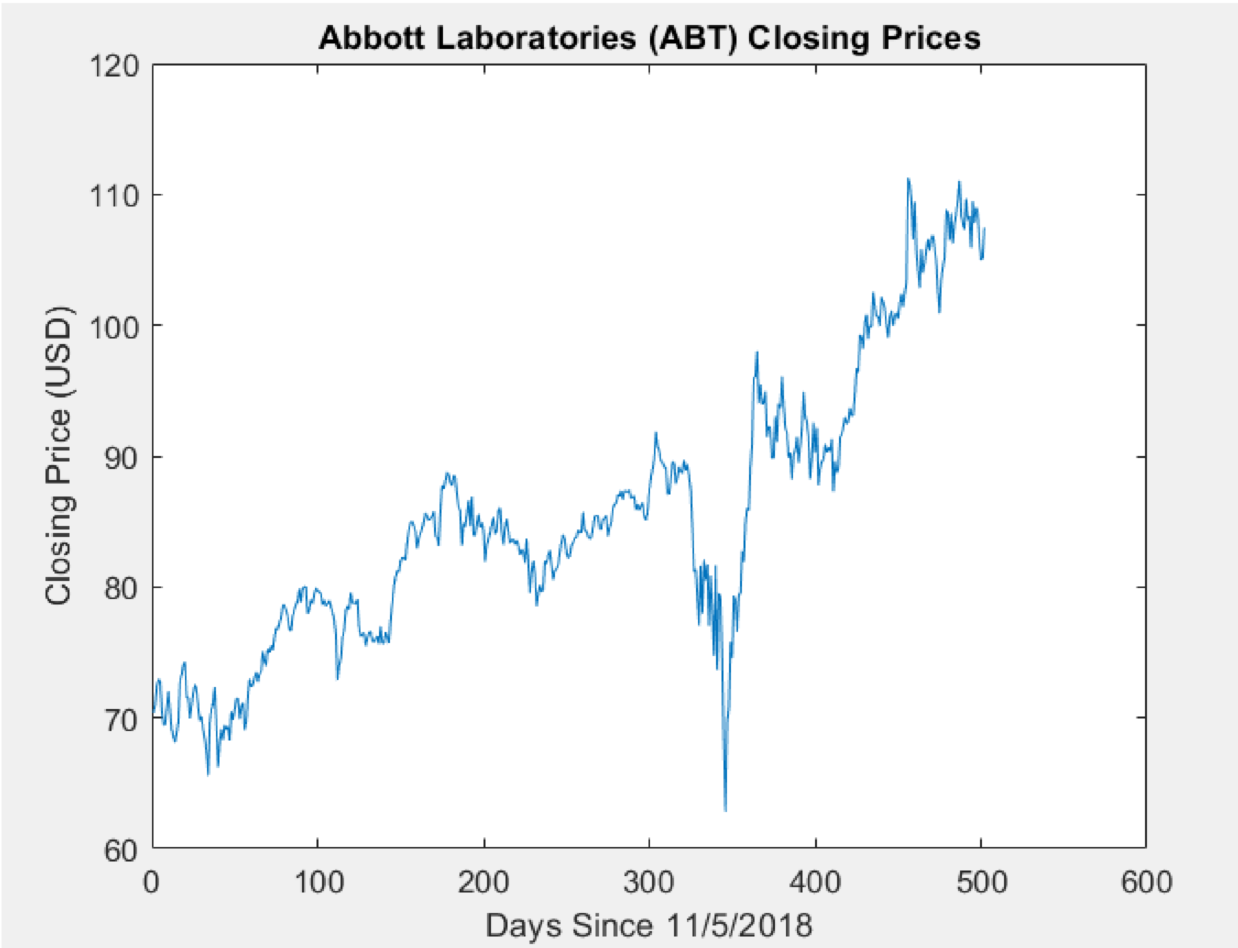
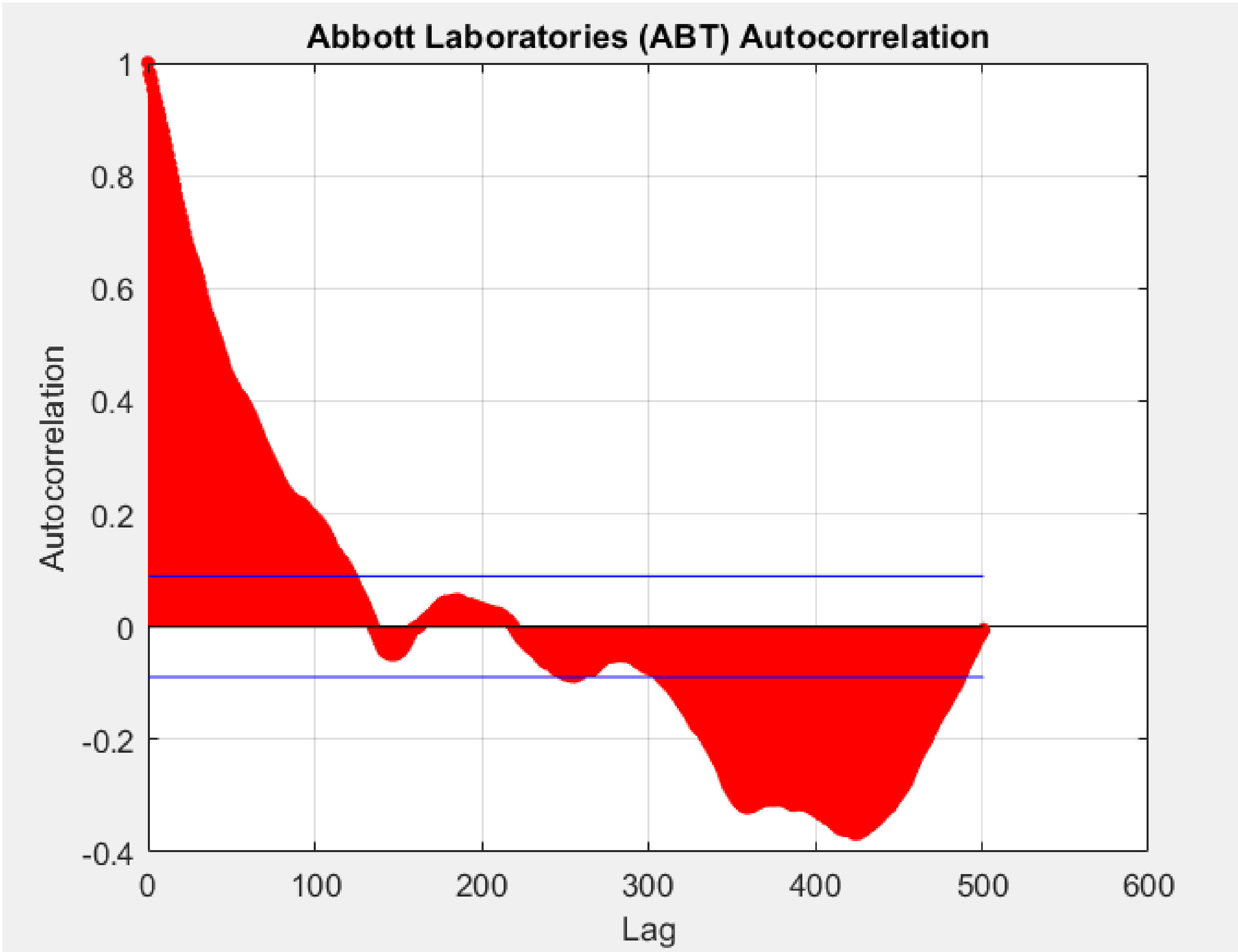
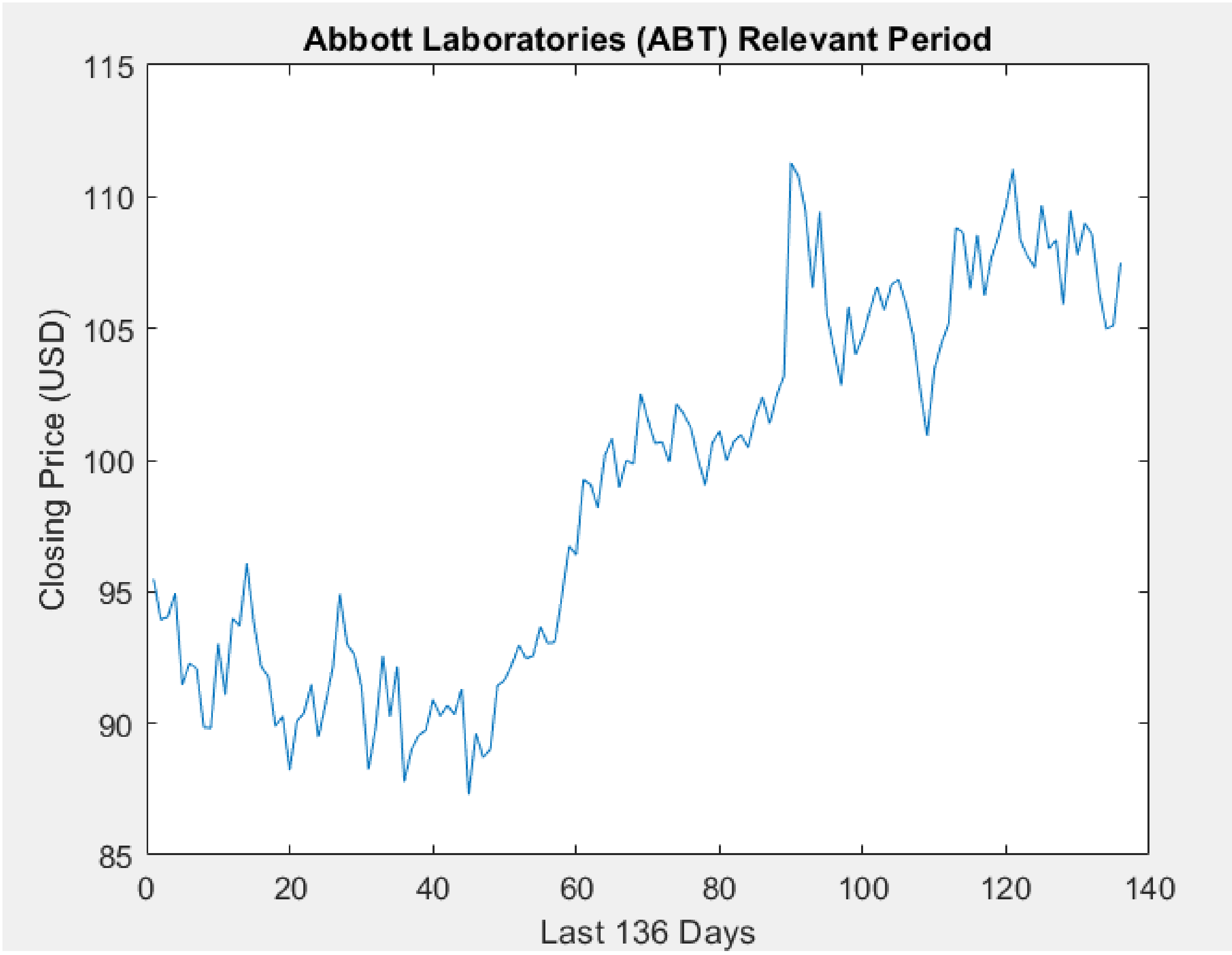
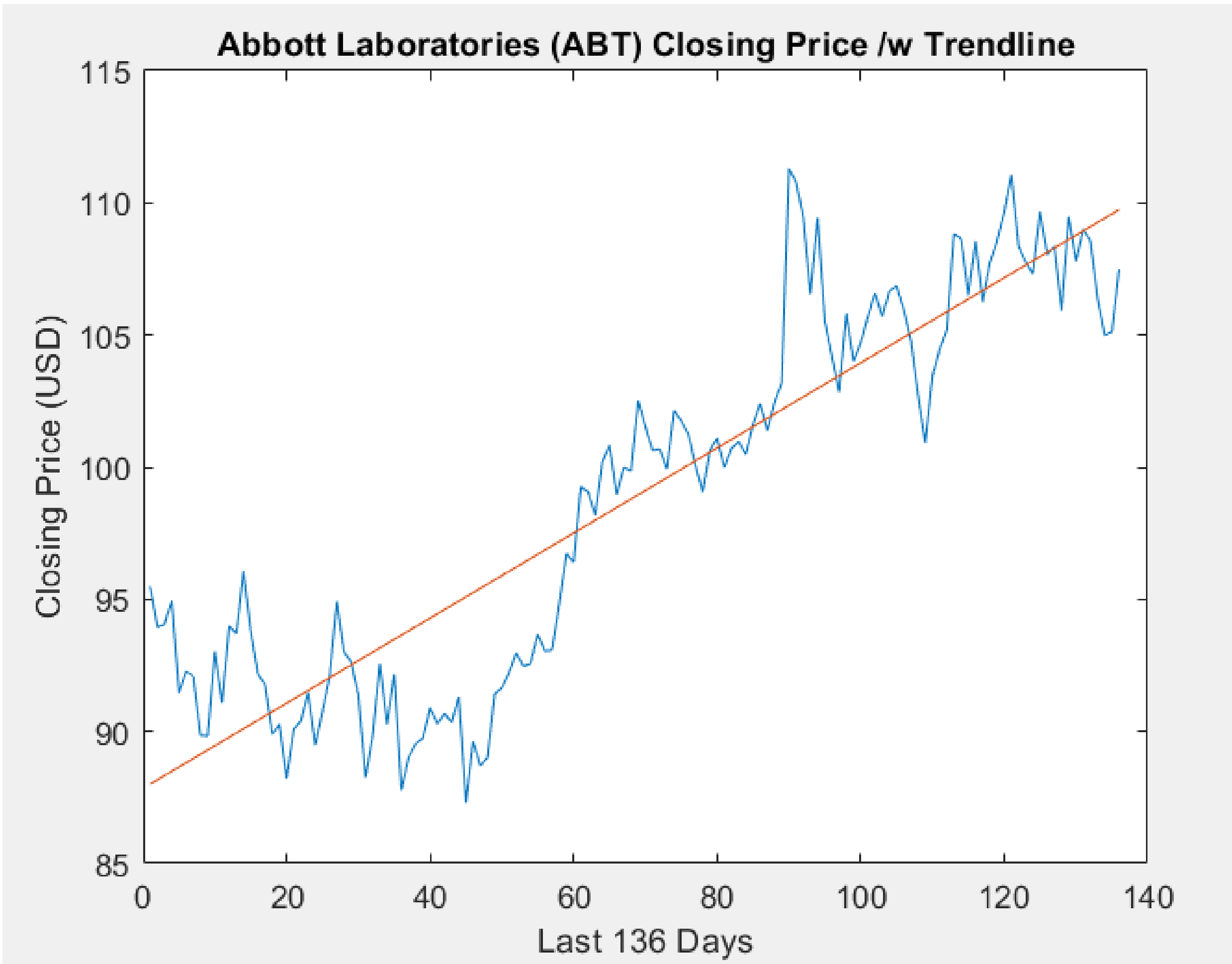
Appendices

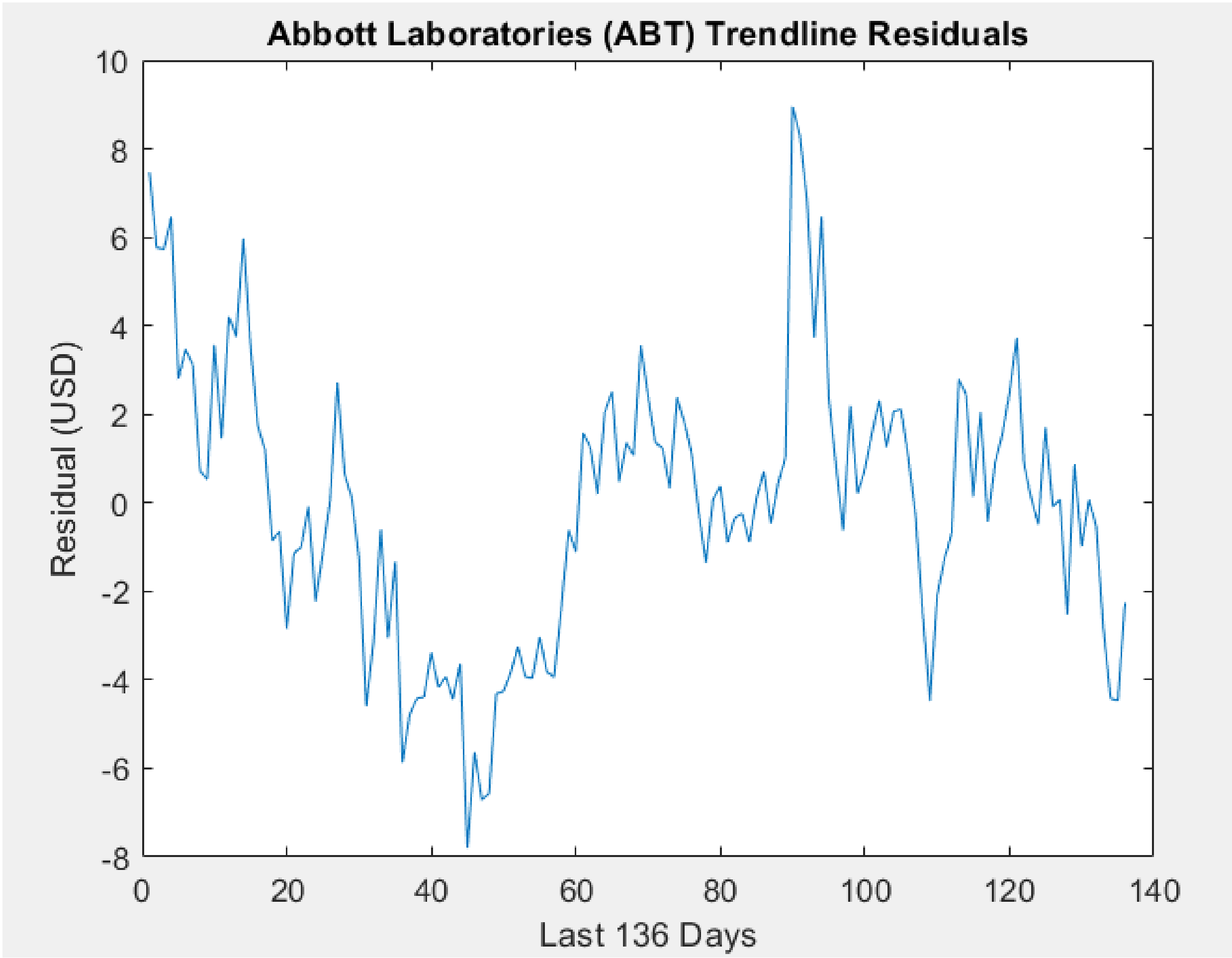


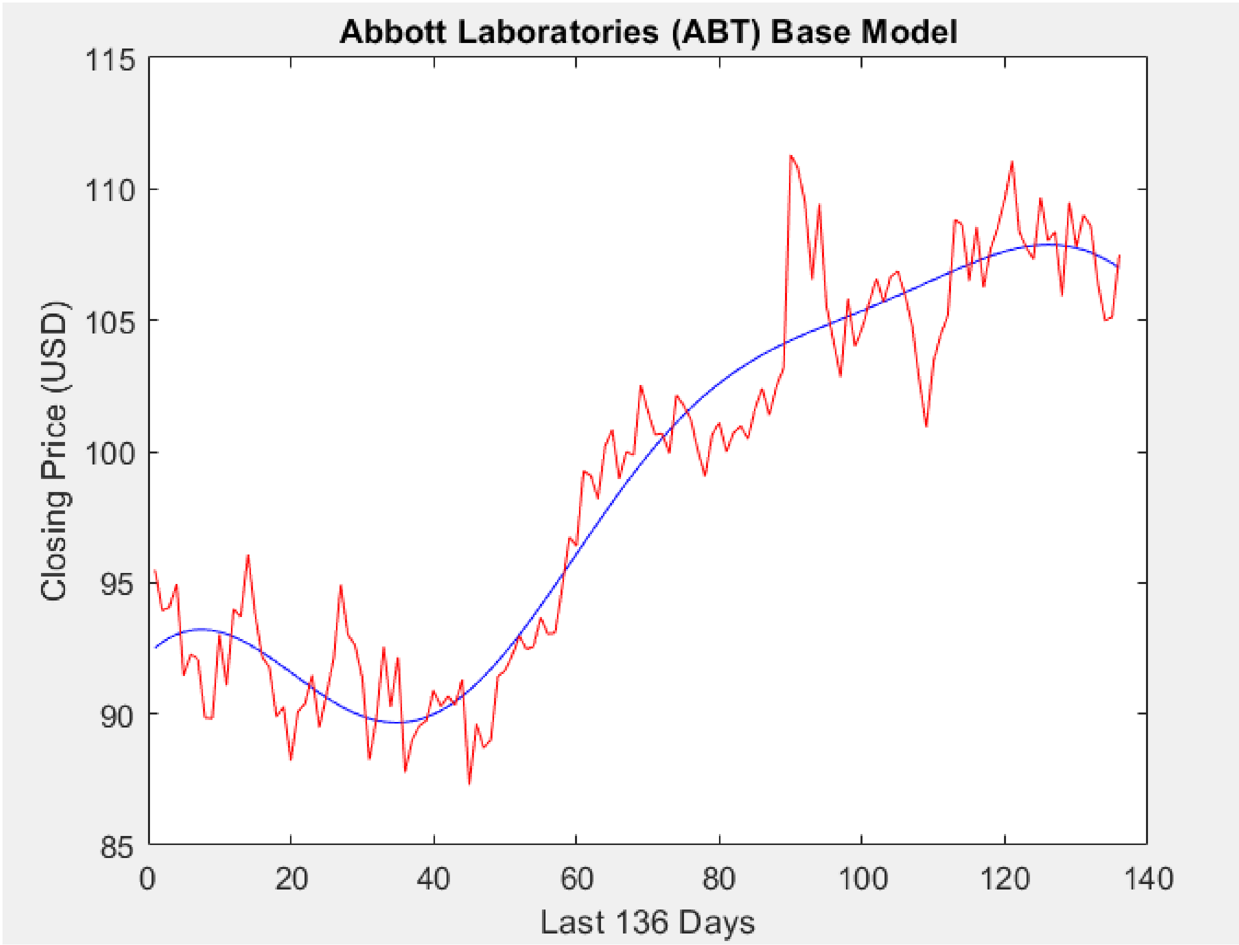
Abbott Laboratories (ABT) Closing Prices
Closing Price (USD)
120
110
100
90
80
70
60
0
100
200
300
400
500
600
Days Since 11/5/2018

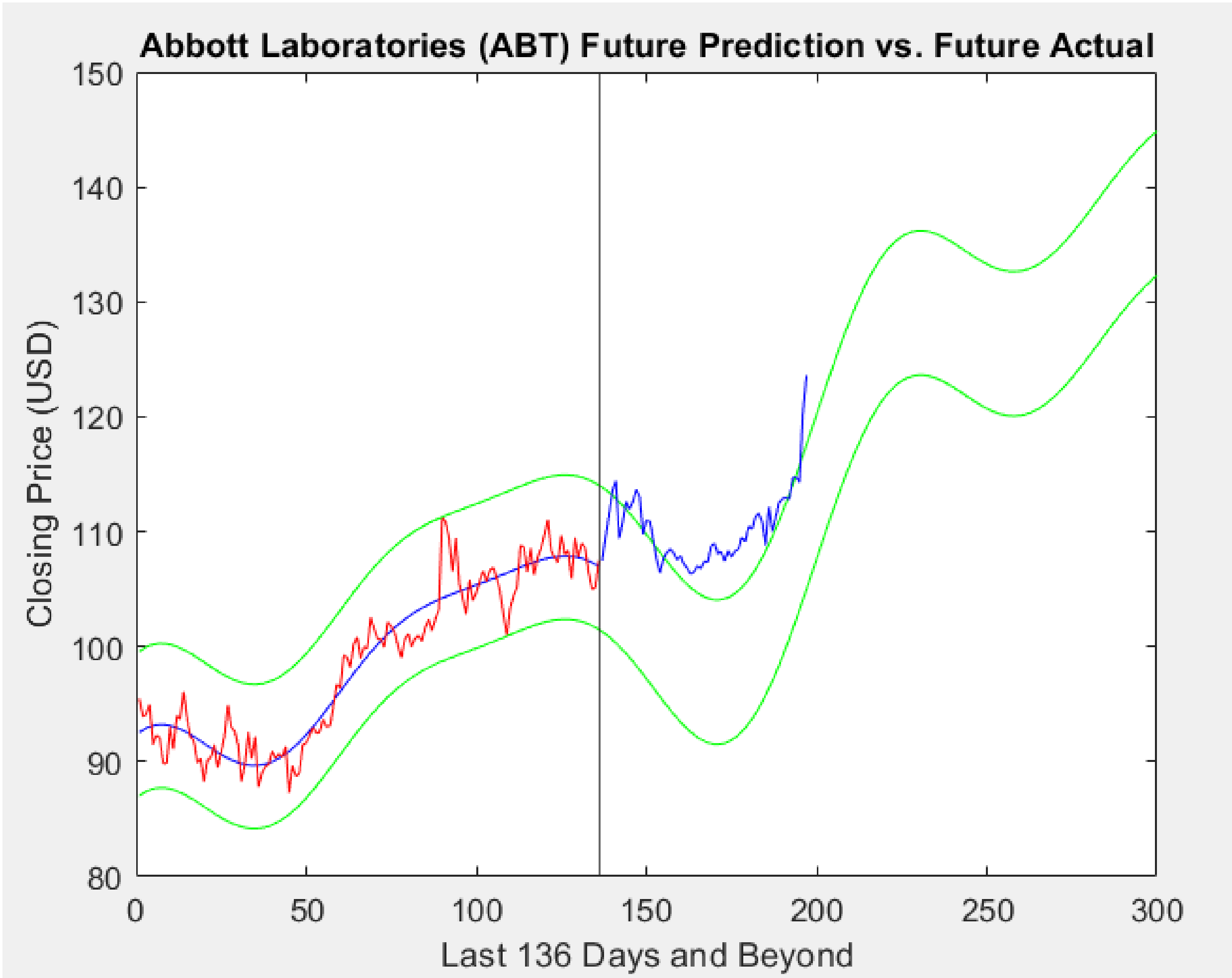

Abbott Laboratories (ABT) Autocorrelation
Autocorrelation
Lag
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
100
200
300
400
500
600

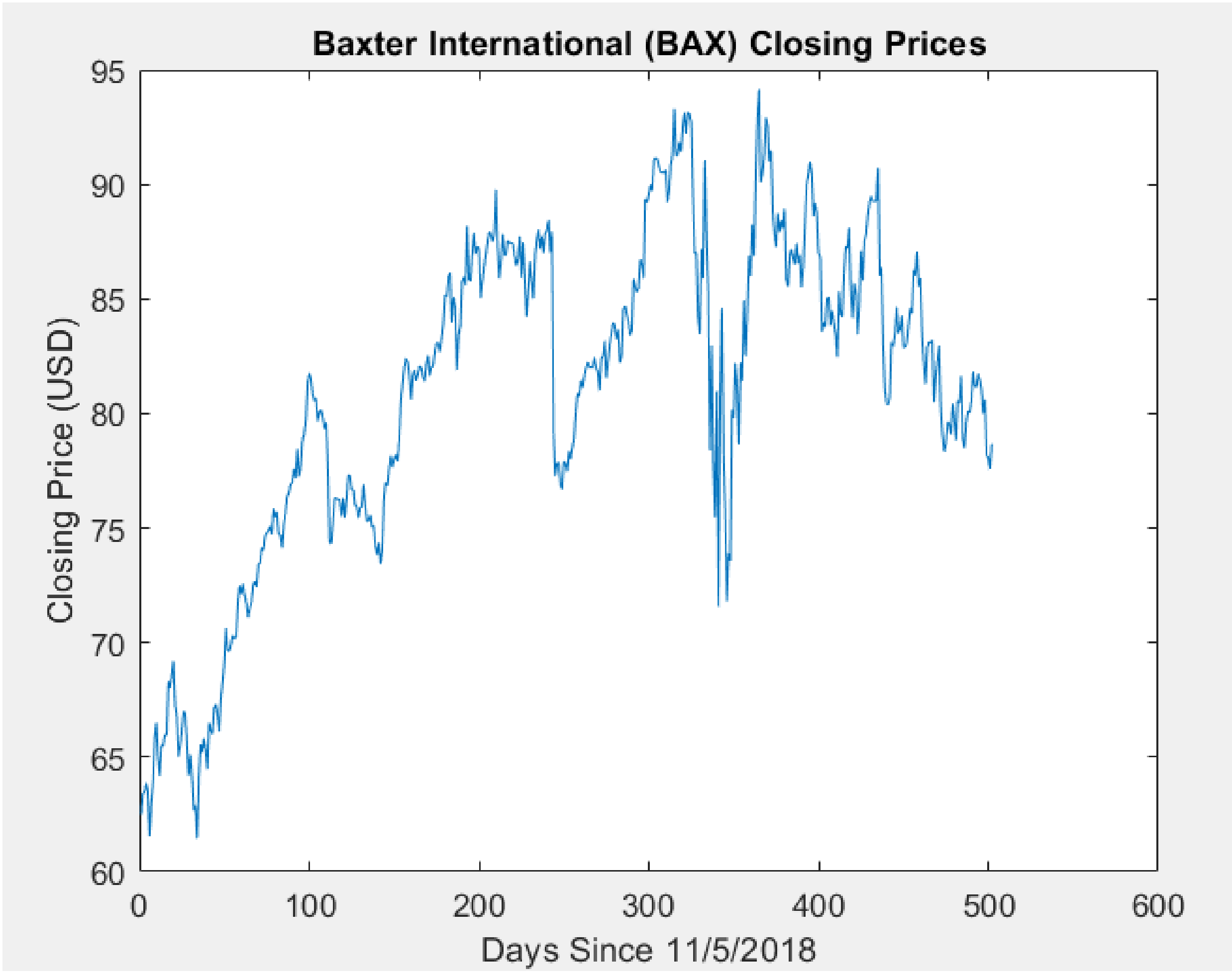

Abbott Laboratories (ABT) Relevant Period
Closing Price (USD)
Last 136 Days
115
110
105
100
95
90
85
0
20
40
60
80
100
120
140

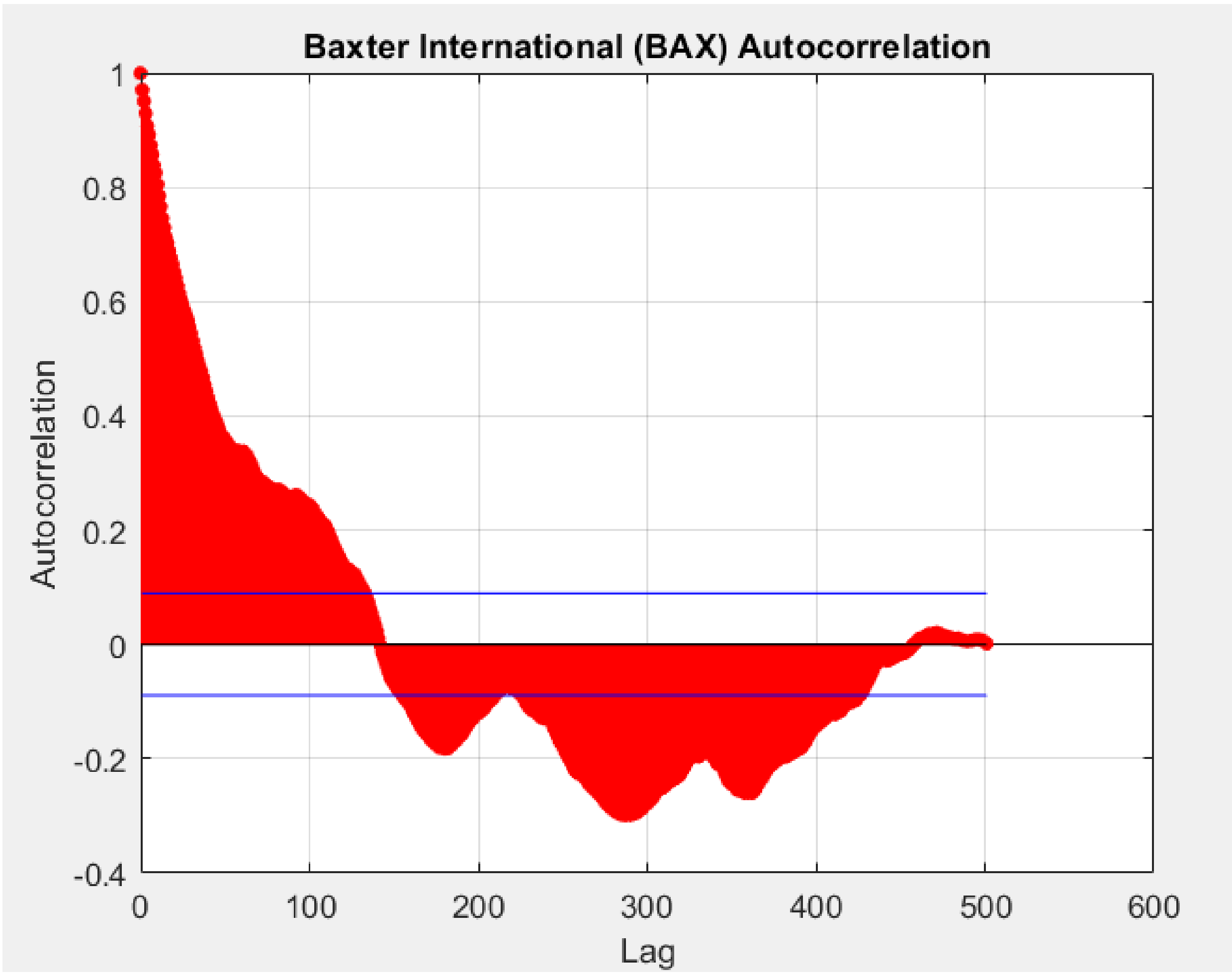

Abbott Laboratories (ABT) Closing Price /w Trendline
Closing Price (USD)
115
110
105
100
95
90
85
0
20
40
60
80
100
120
140
Last 136 Days

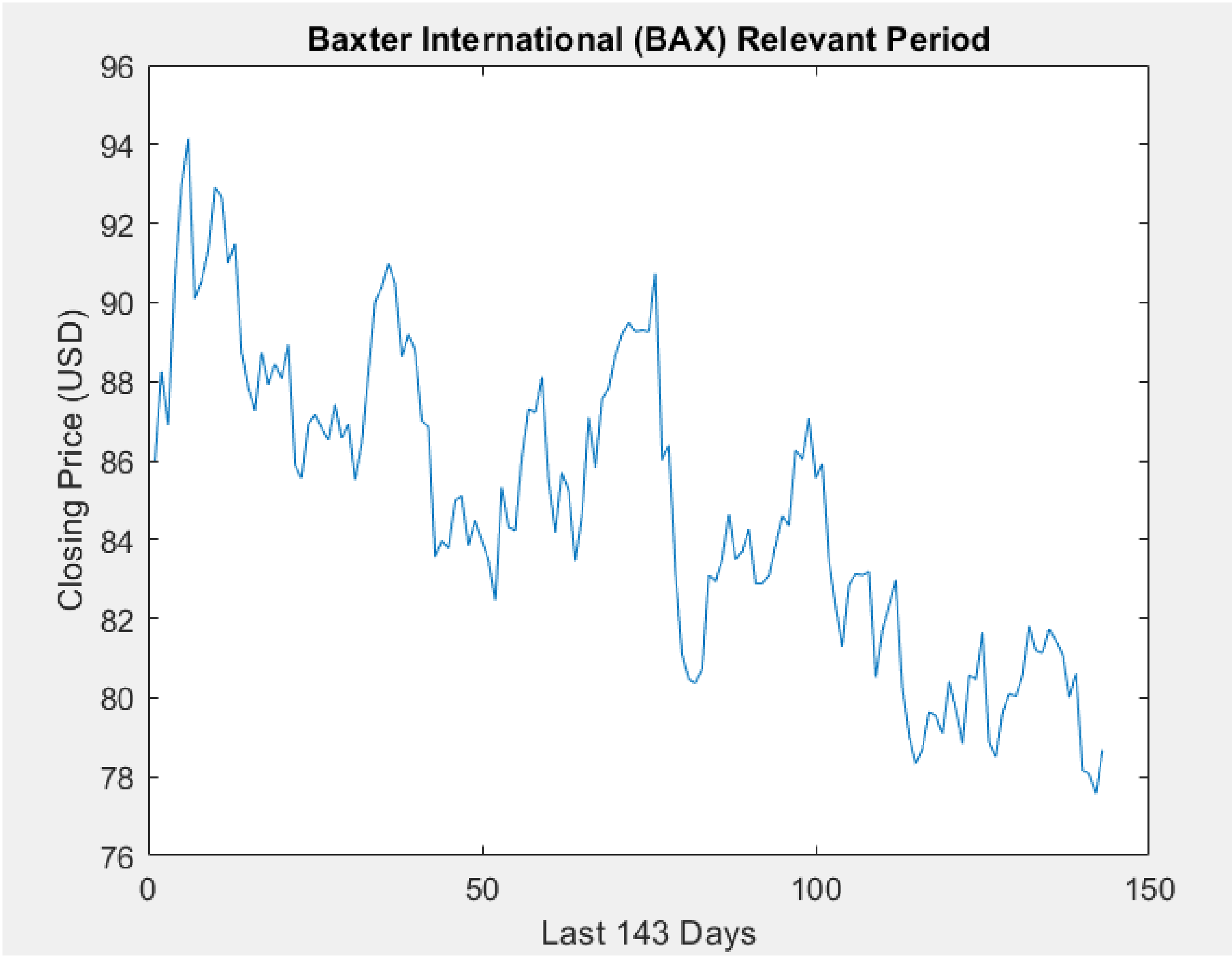

Abbott Laboratories (ABT) Trendline Residuals
Residual (USD)
Last 136 Days
10
8
6
4
2
0
-2
-4
-6
-8
0
20
40
60
80
100
120
140

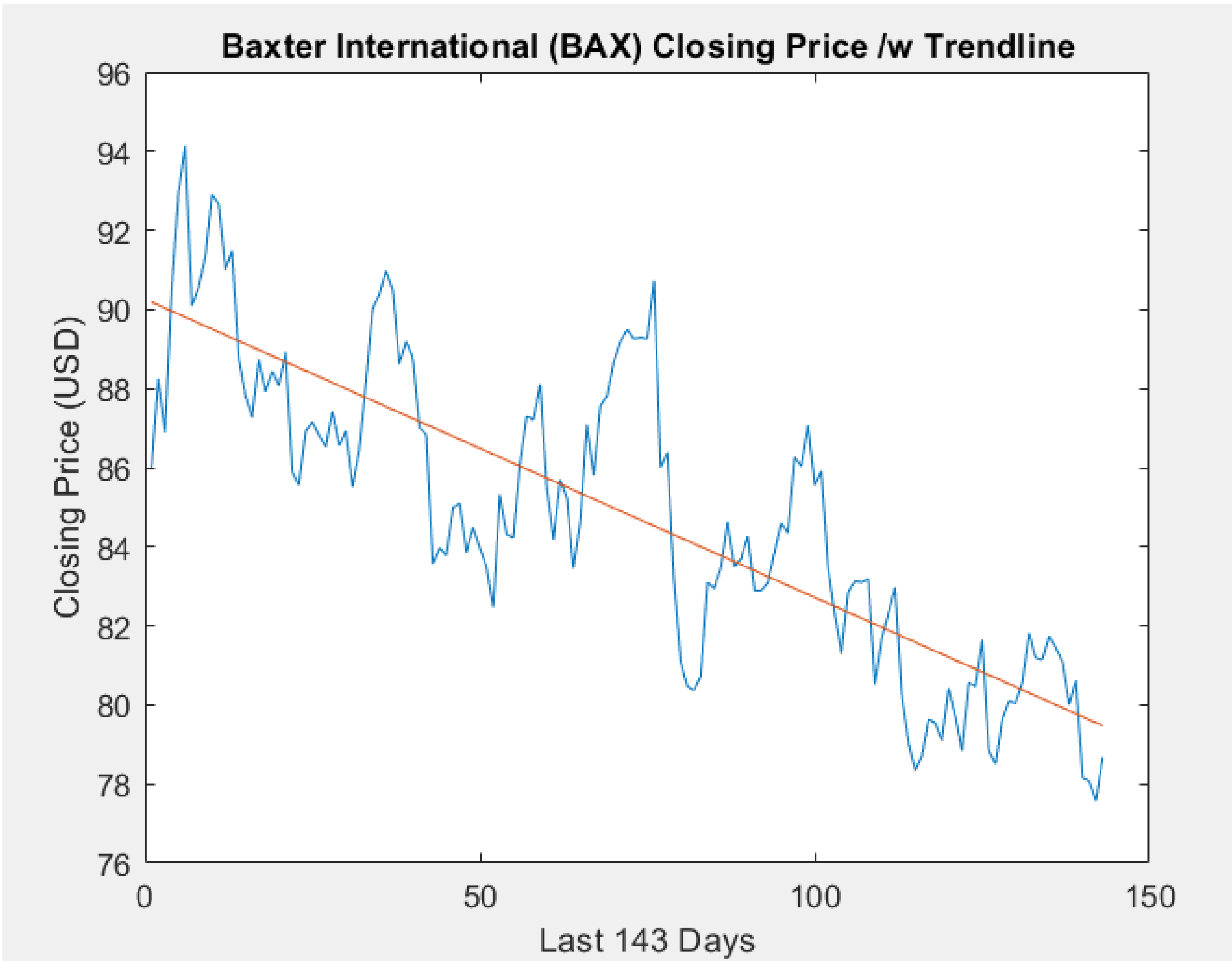

Abbott Laboratories (ABT) Base Model
Closing Price (USD)
115
110
105
100
95
90
85
0
20
40
60
80
100
120
140
Last 136 Days

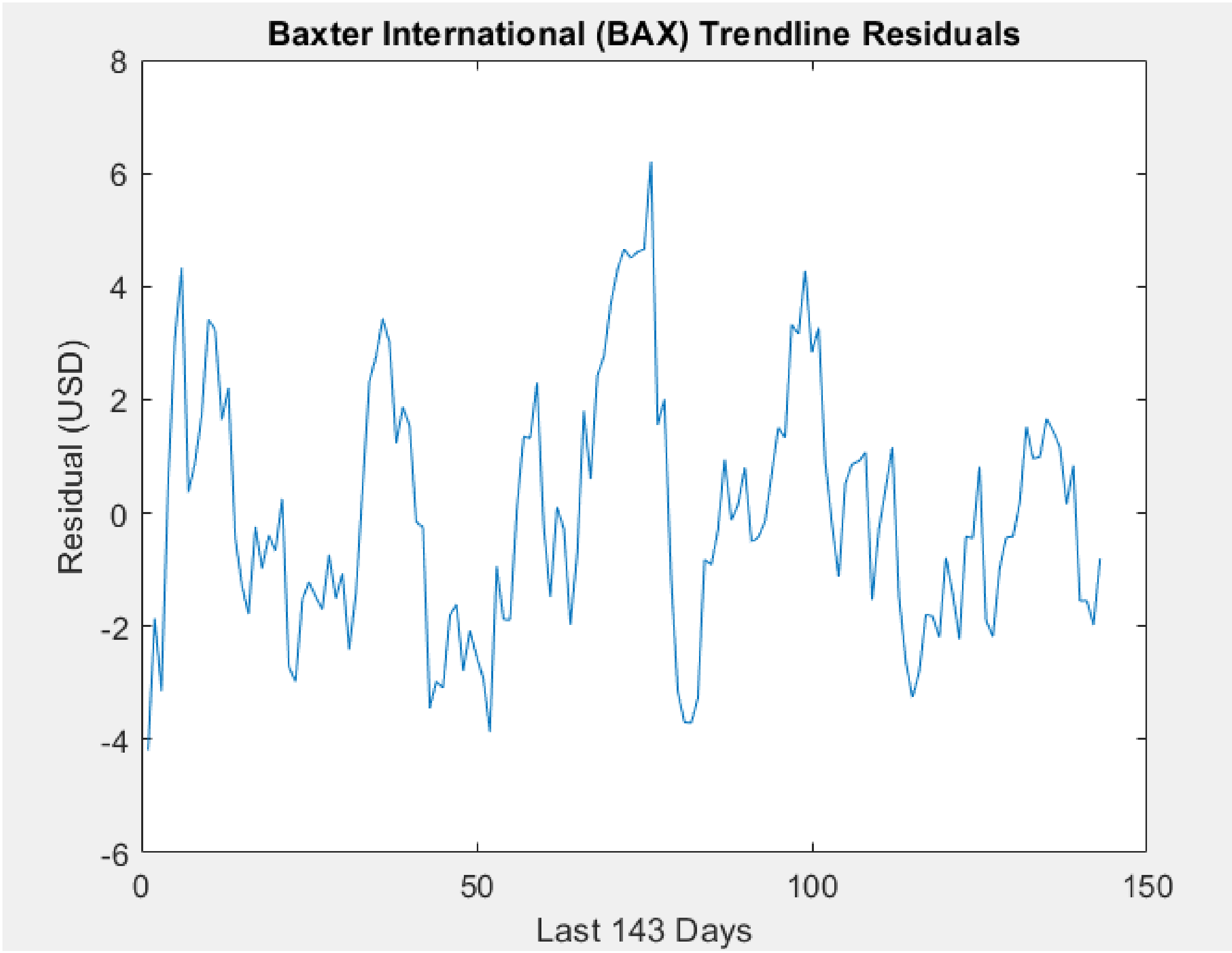

Abbott Laboratories (ABT) Future Prediction vs. Future Actual
Closing Price (USD)
150
140
130
120
110
100
90
80
0
50
100
150
200
250
300
Last 136 Days and Beyond

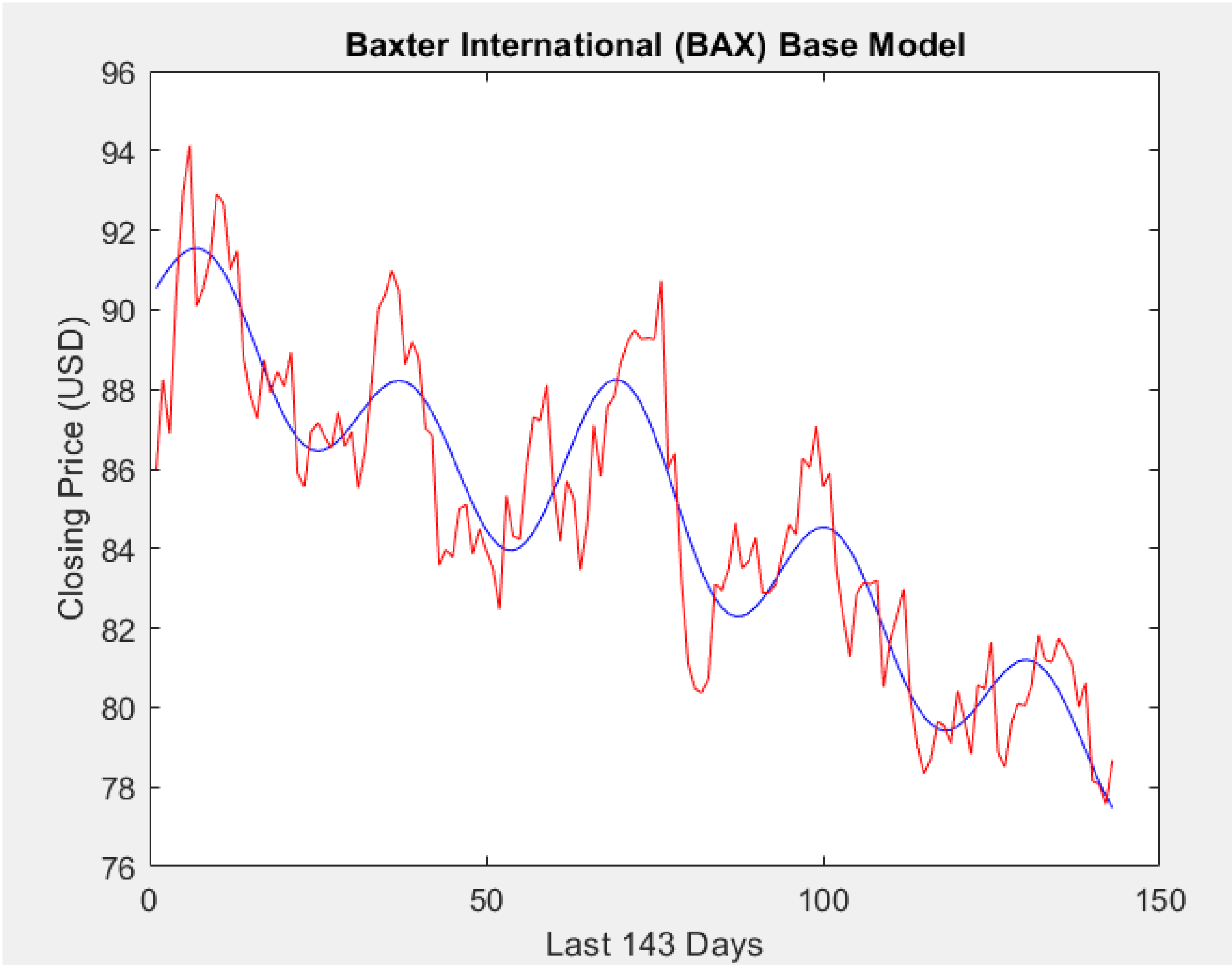

Baxter International (BAX) Closing Prices
Closing Price (USD)
Days Since 11/5/2018
95
90
85
80
75
70
65
60
0
100
200
300
400
500
600

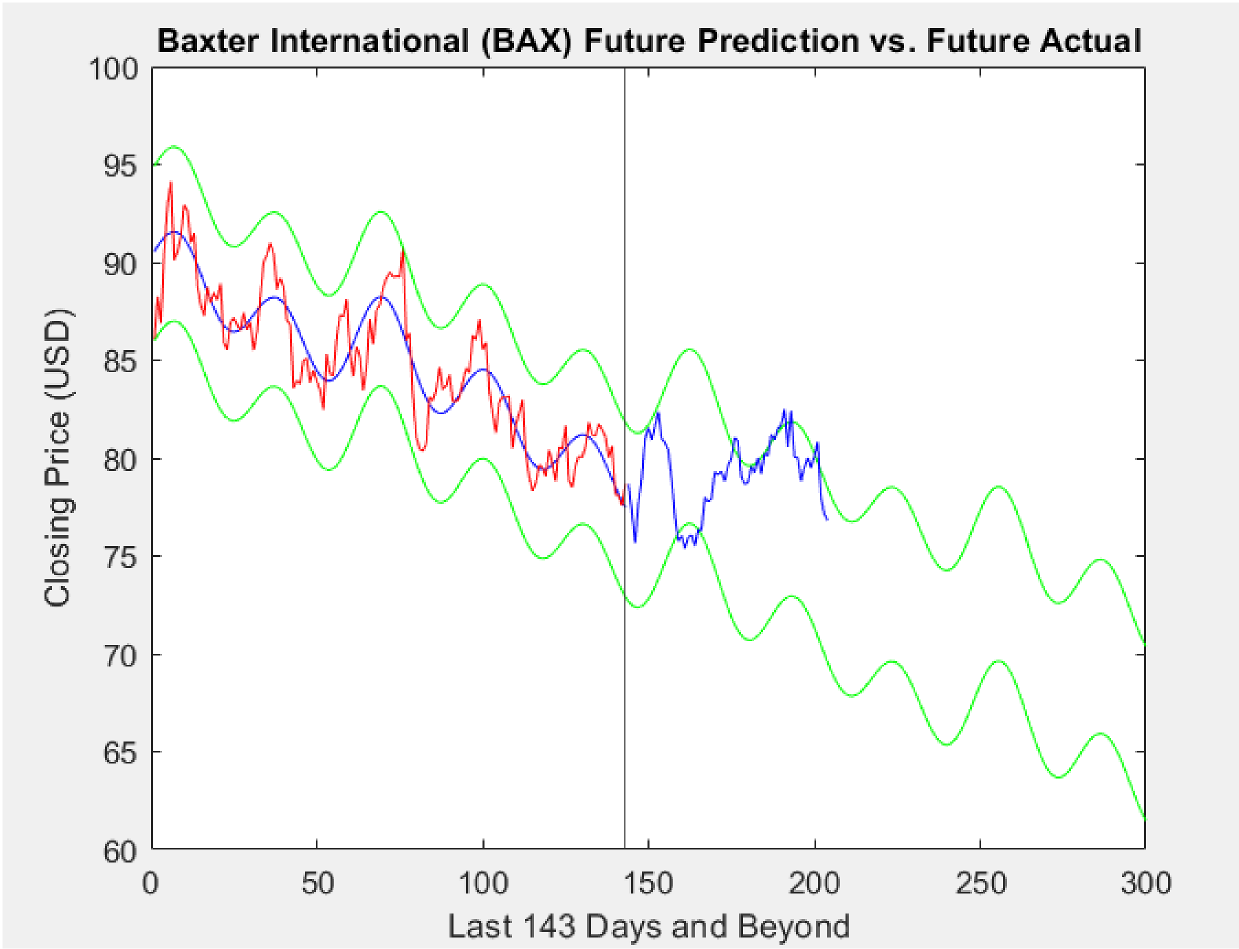

Baxter International (BAX) Autocorrelation
Autocorrelation
Lag
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
100
200
300
400
500
600


Baxter International (BAX) Relevant Period
Closing Price (USD)
96
94
92
90
88
86
84
82
80
78
76
0
50
100
150
Last 143 Days

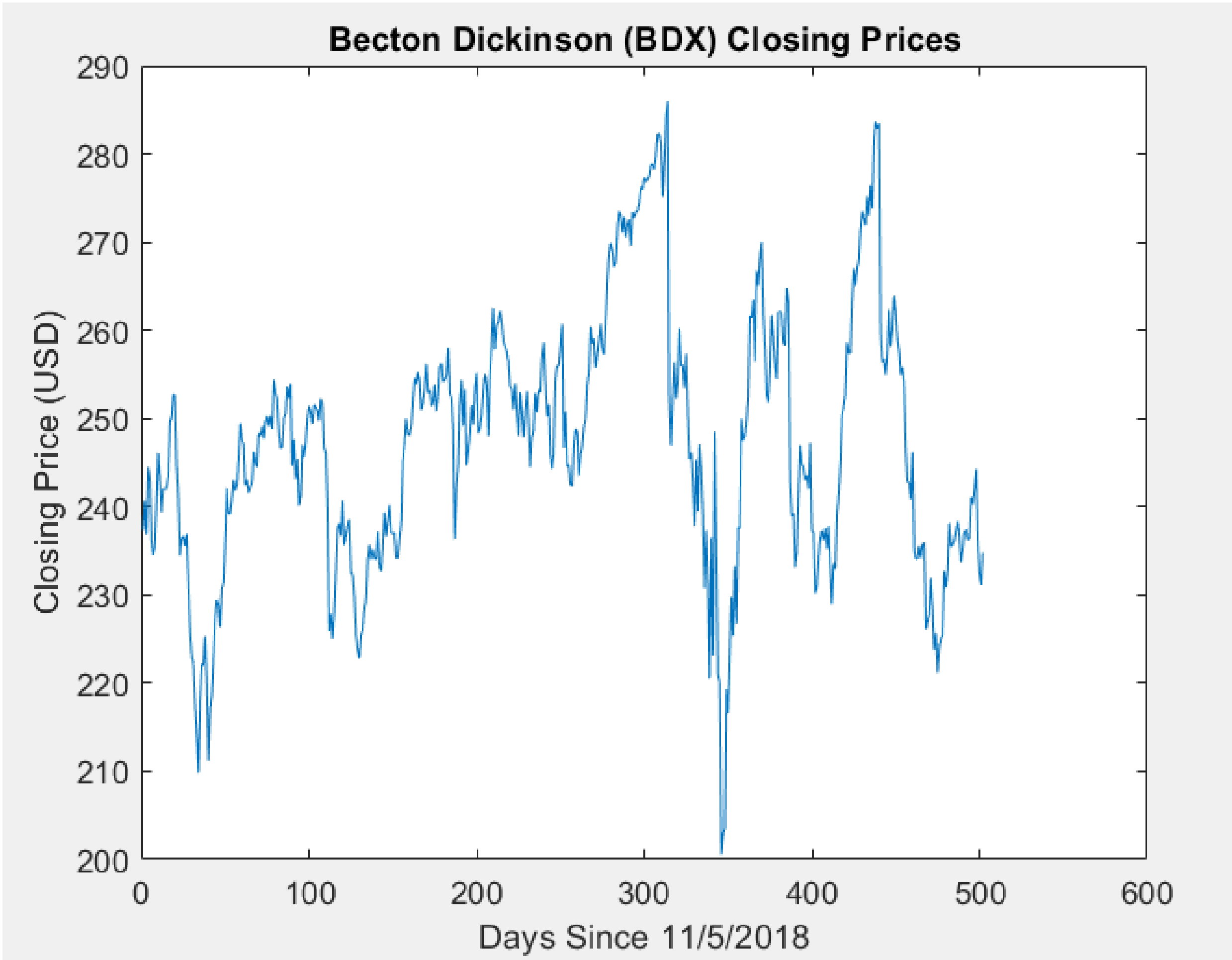

Baxter International (BAX) Closing Price /w Trendline
96
94
92
90
88
86
84
82
80
78
76
Closing Price (USD)
0
50
100
150
Last 143 Days


Baxter International (BAX) Trendline Residuals
Residual (USD)
Last 143 Days
8
6
4
2
0
-2
-4
-6
0
50
100
150

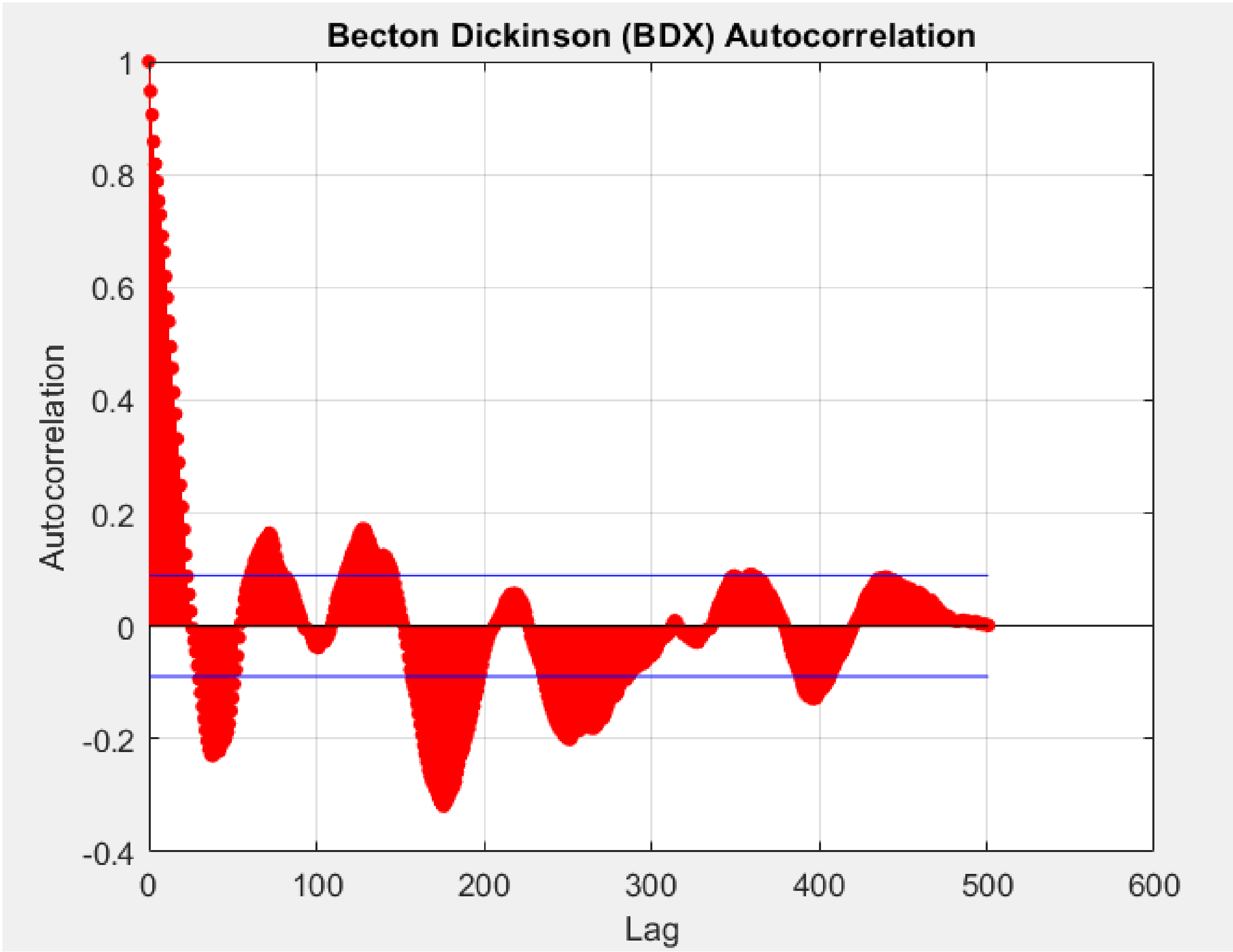

Baxter International (BAX) Base Model
Closing Price (USD)
Last 143 Days
96
94
92
90
88
86
84
82
80
78
76
0
50
100
150



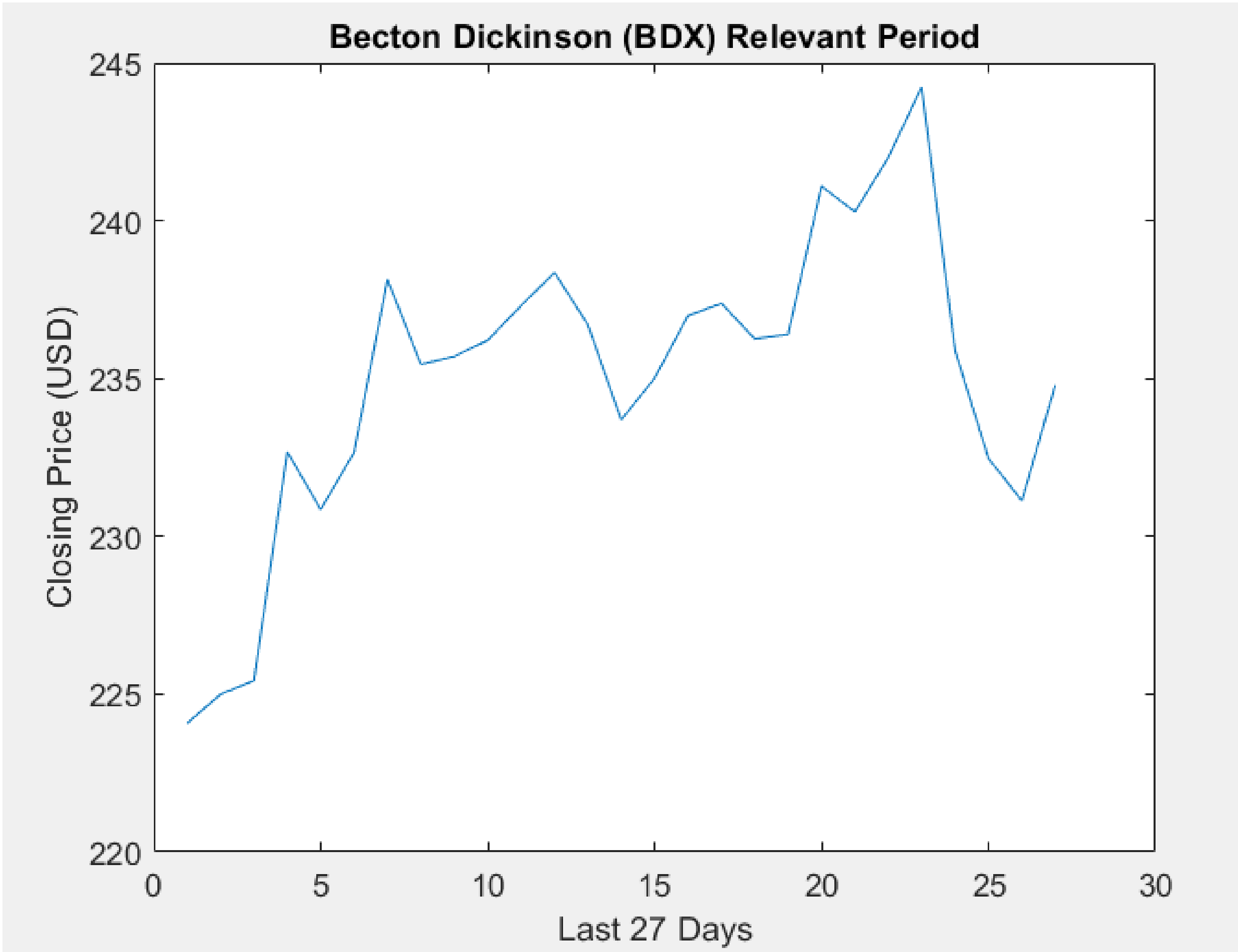
Baxter International (BAX) Future Prediction vs. Future Actual
Closing Price (USD)
Last 143 Days and Beyond
100
95
90
85
80
75
70
65
60
0
50
100
150
200
250
300

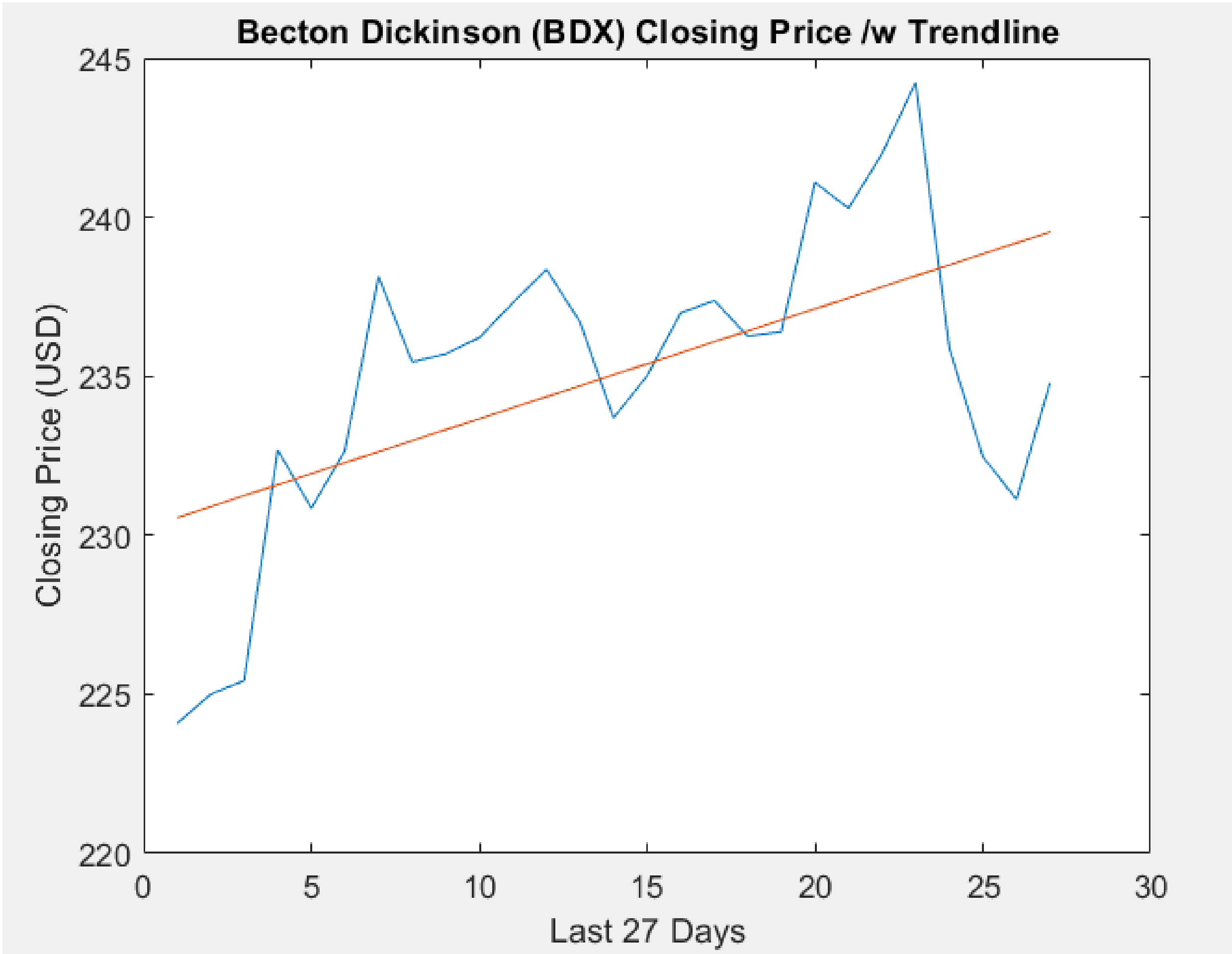


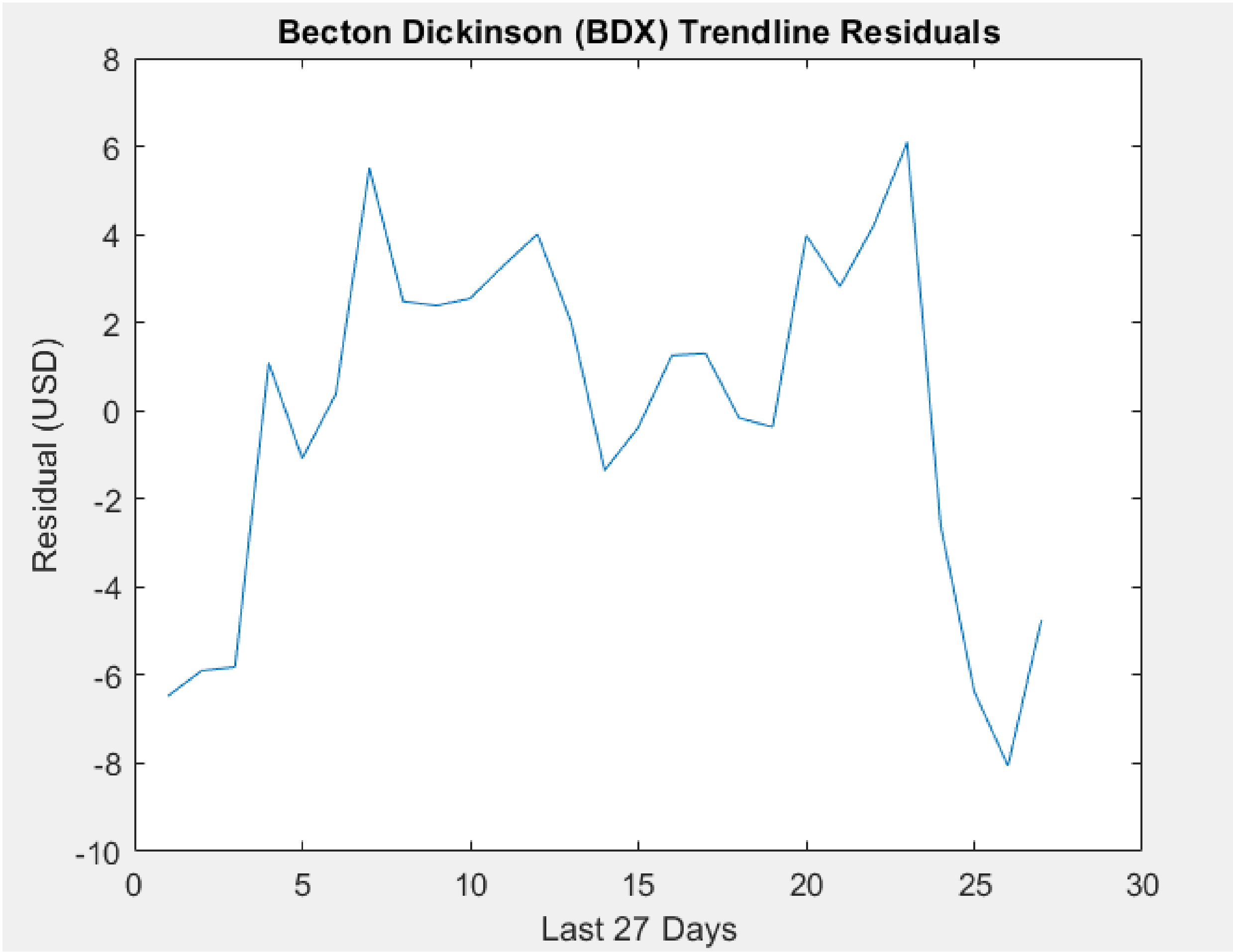
Becton Dickinson (BDX) Closing Prices
Closing Price (USD)
Days Since 11/5/2018
290
280
270
260
250
240
230
220
210
200
0
100
200
300
400
500
600

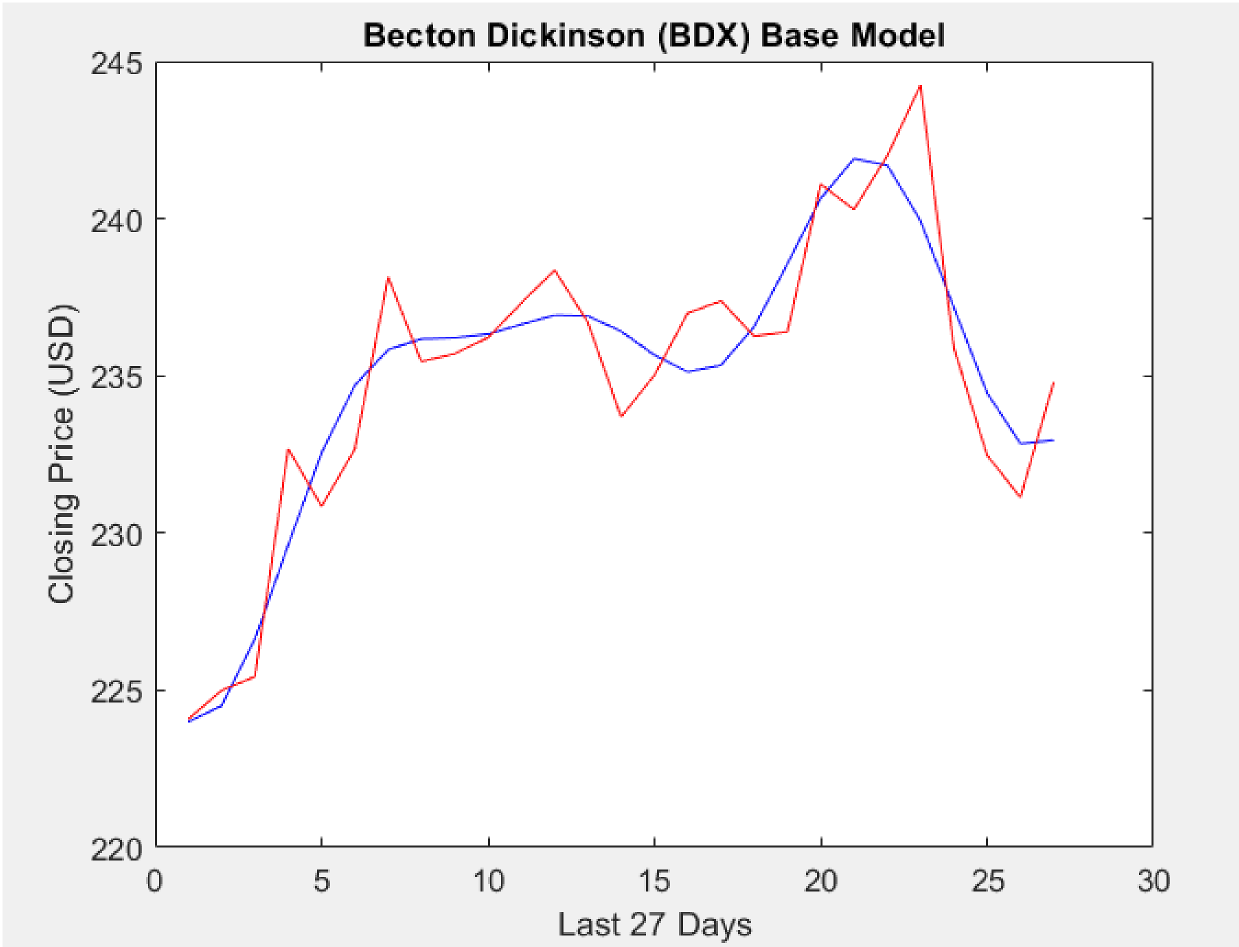


Becton Dickinson (BDX) Autocorrelation
Autocorrelation
Lag
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
100
200
300
400
500
600

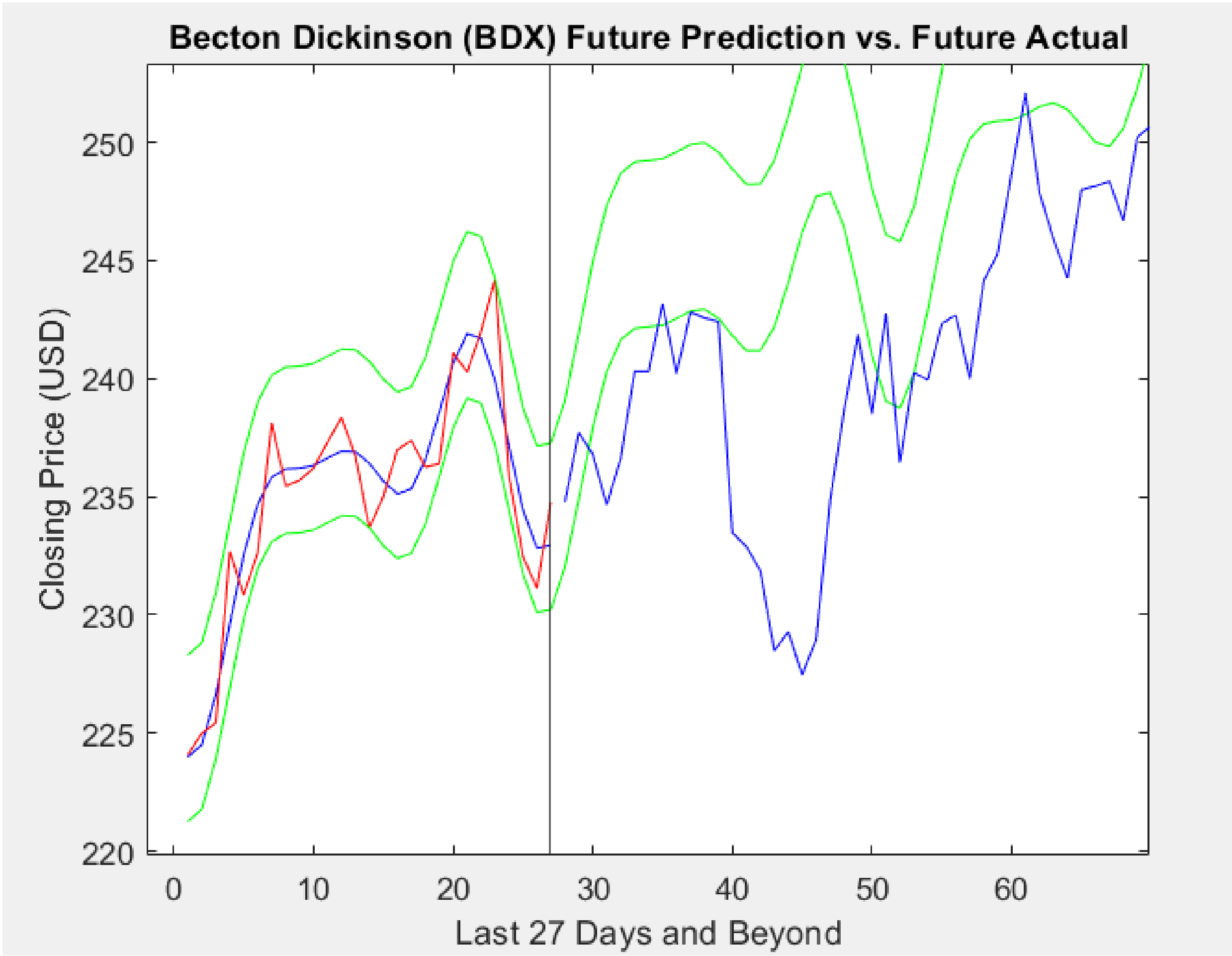

Becton Dickinson (BDX) Relevant Period
Closing Price (USD)
245
240
235
230
225
220
0
5
10
15
20
25
30
Last 27 Days

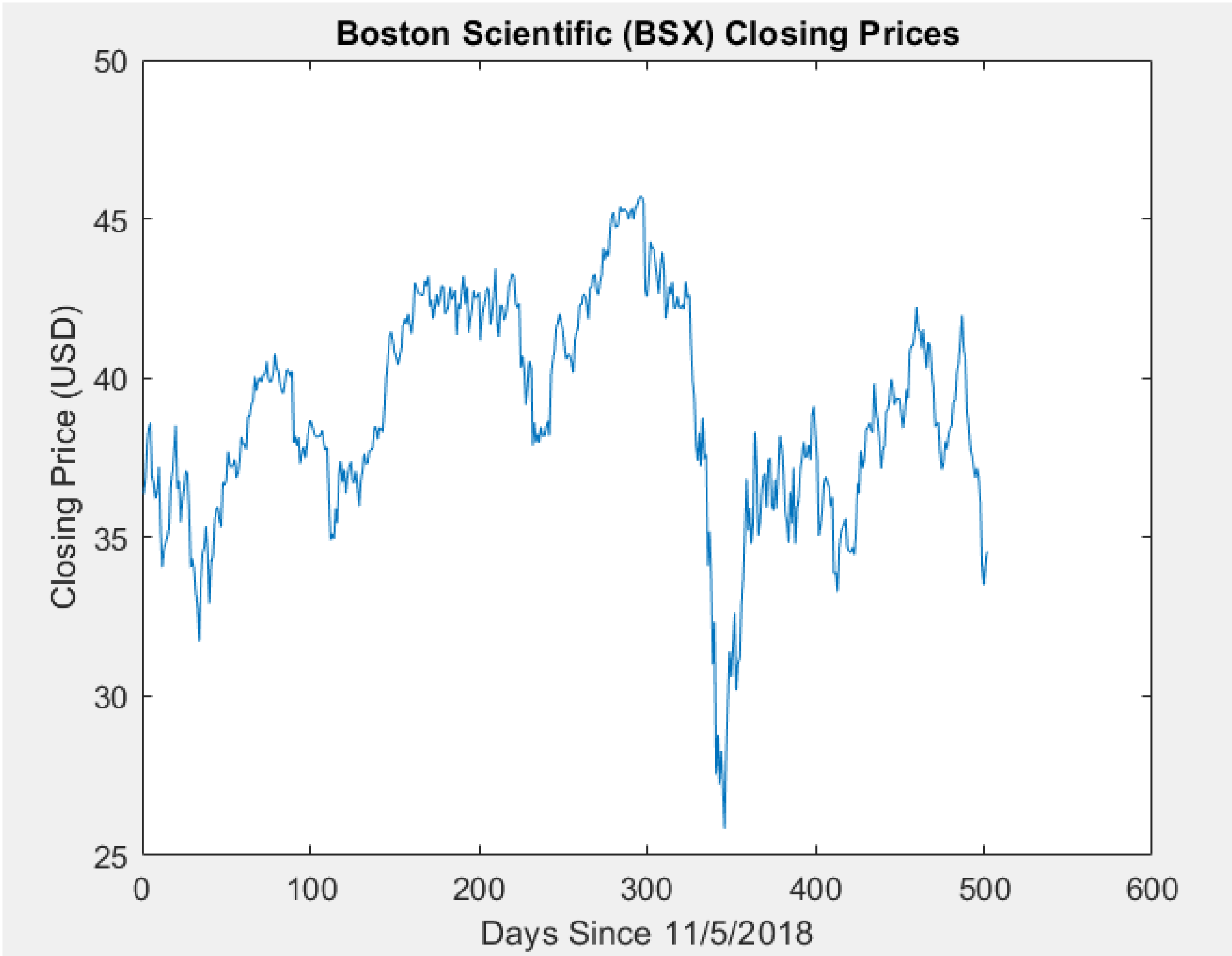

Becton Dickinson (BDX) Closing Price /w Trendline
245
240
235
230
225
220
Closing Price (USD)
0
5
10
15
20
25
30
Last 27 Days

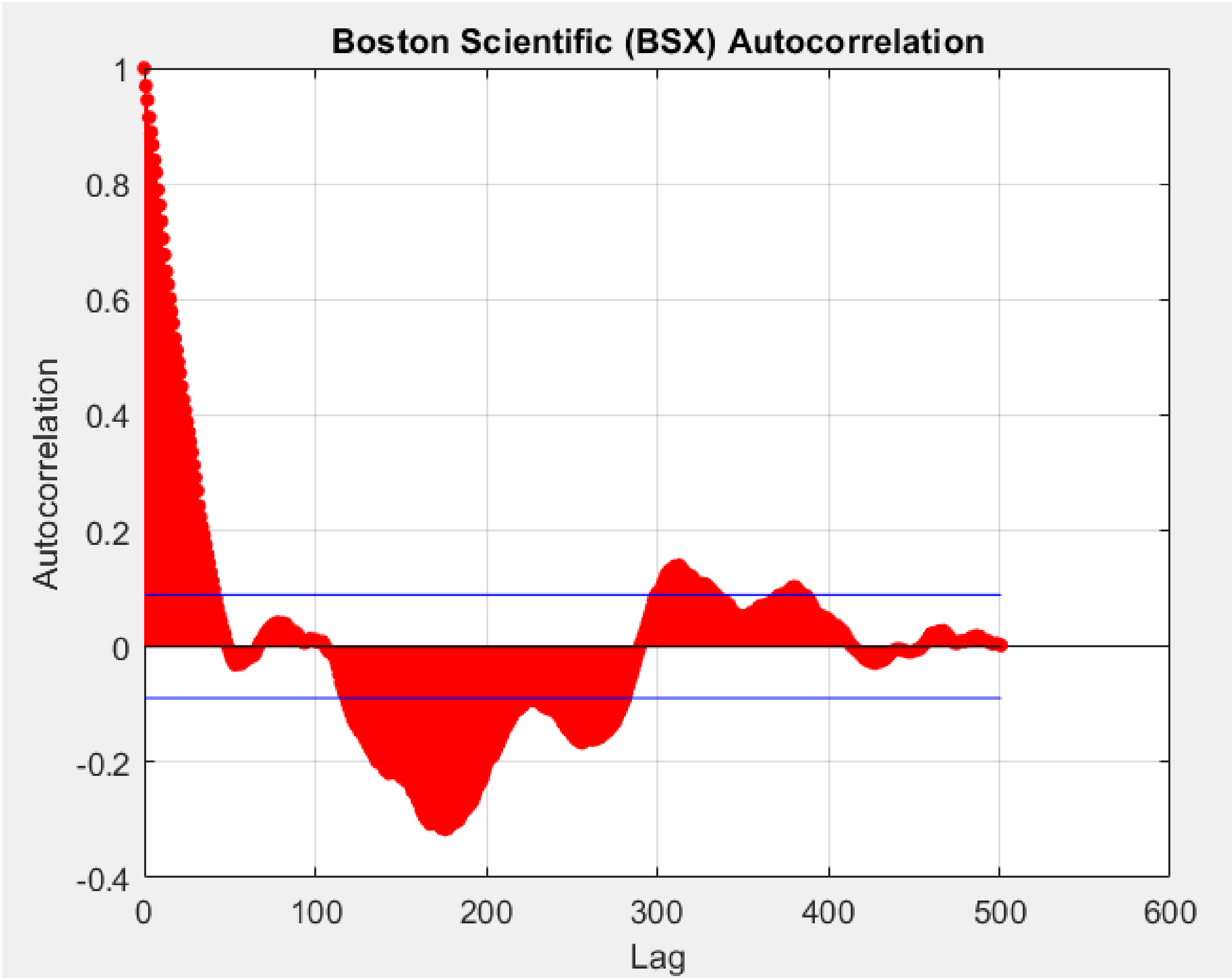

Becton Dickinson (BDX) Trendline Residuals
Residual (USD)
8
6
4
2
0
-2
-4
-6
-8
-10
0
5
10
15
20
25
30
Last 27 Days

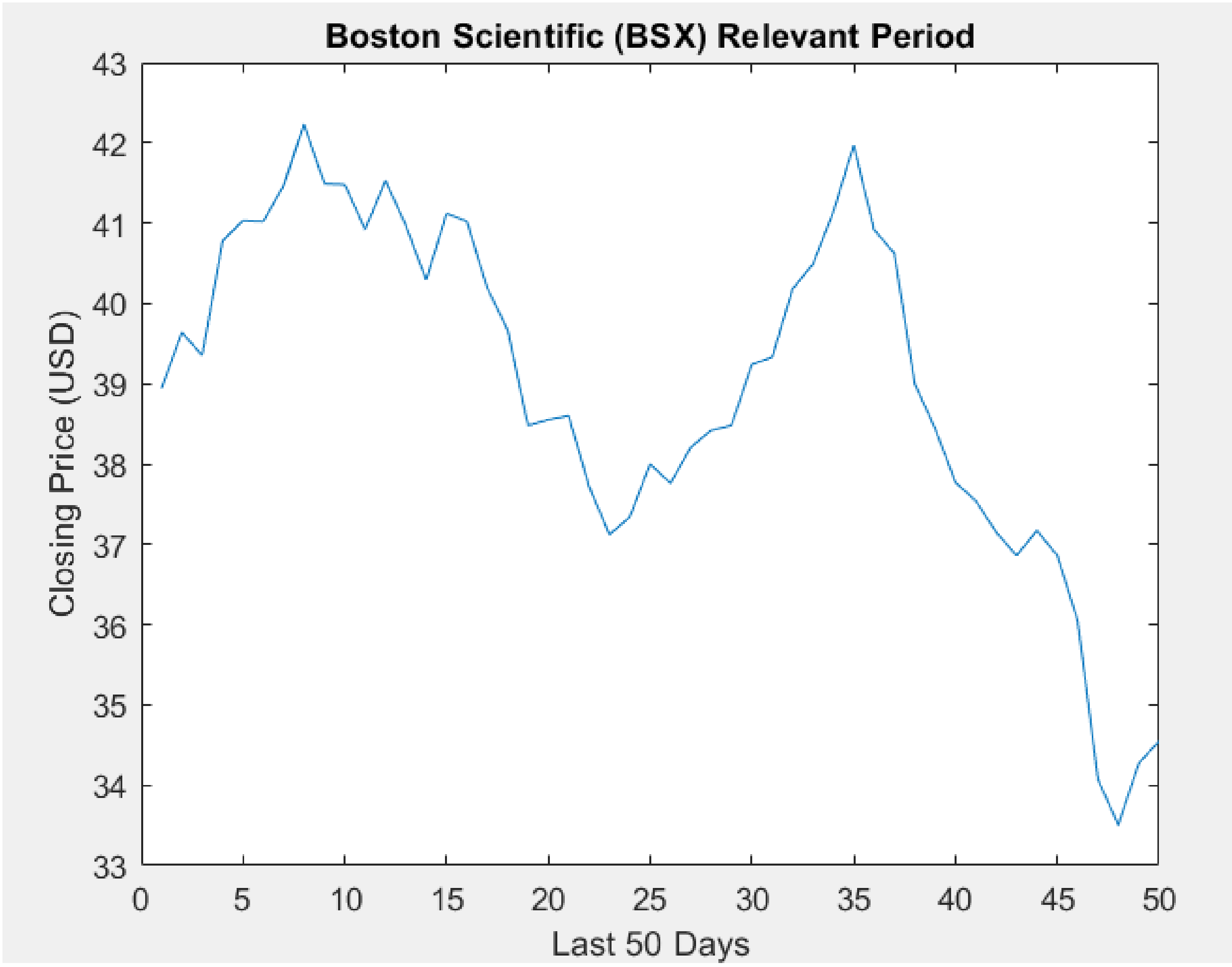


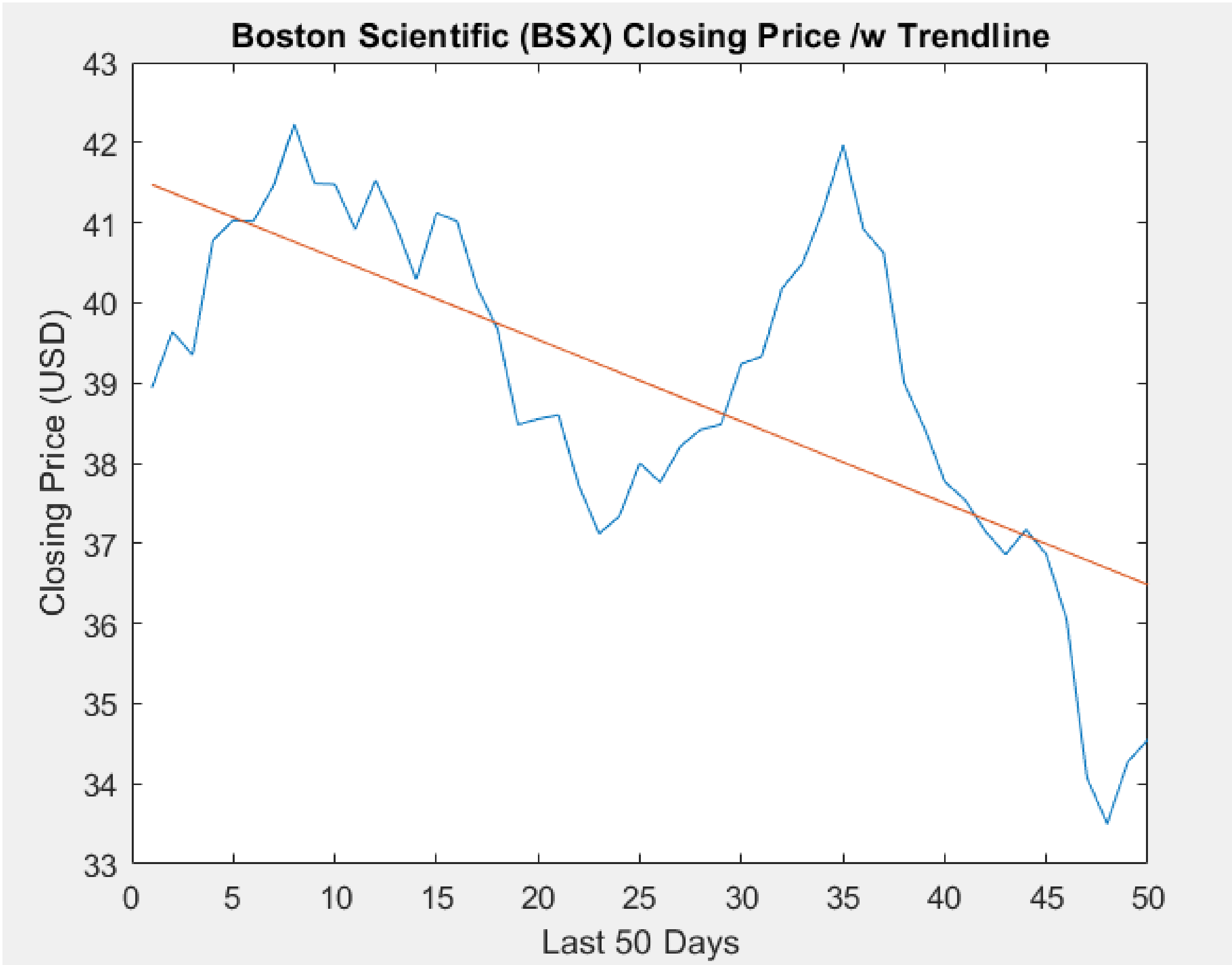
Becton Dickinson (BDX) Base Model
Closing Price (USD)
245
240
235
230
225
220
0
5
10
15
20
25
30
Last 27 Days

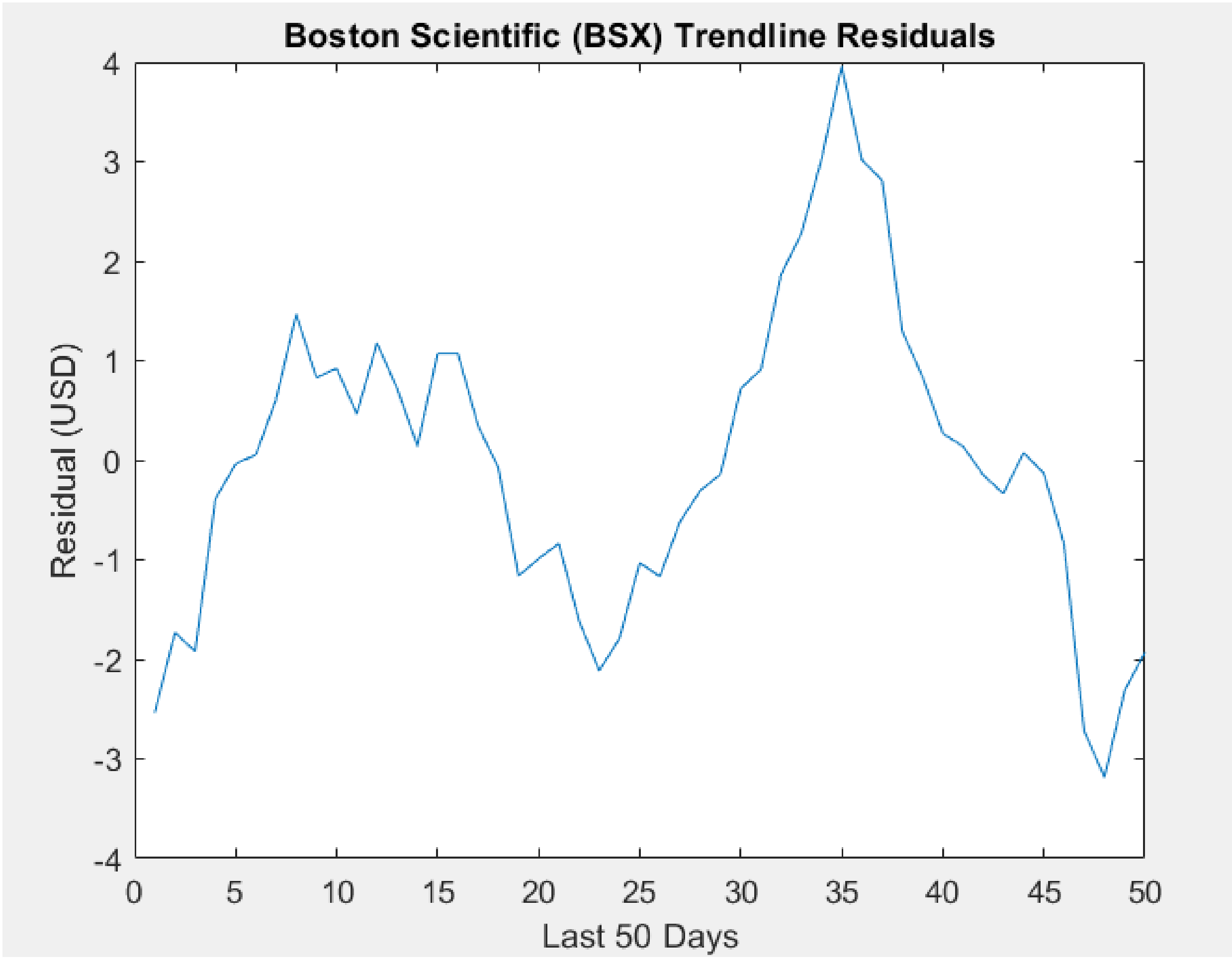

Becton Dickinson (BDX) Future Prediction vs. Future Actual
Closing Price (USD)
250
245
240
235
230
225
220
0
10
20
30
40
50
60
Last 27 Days and Beyond

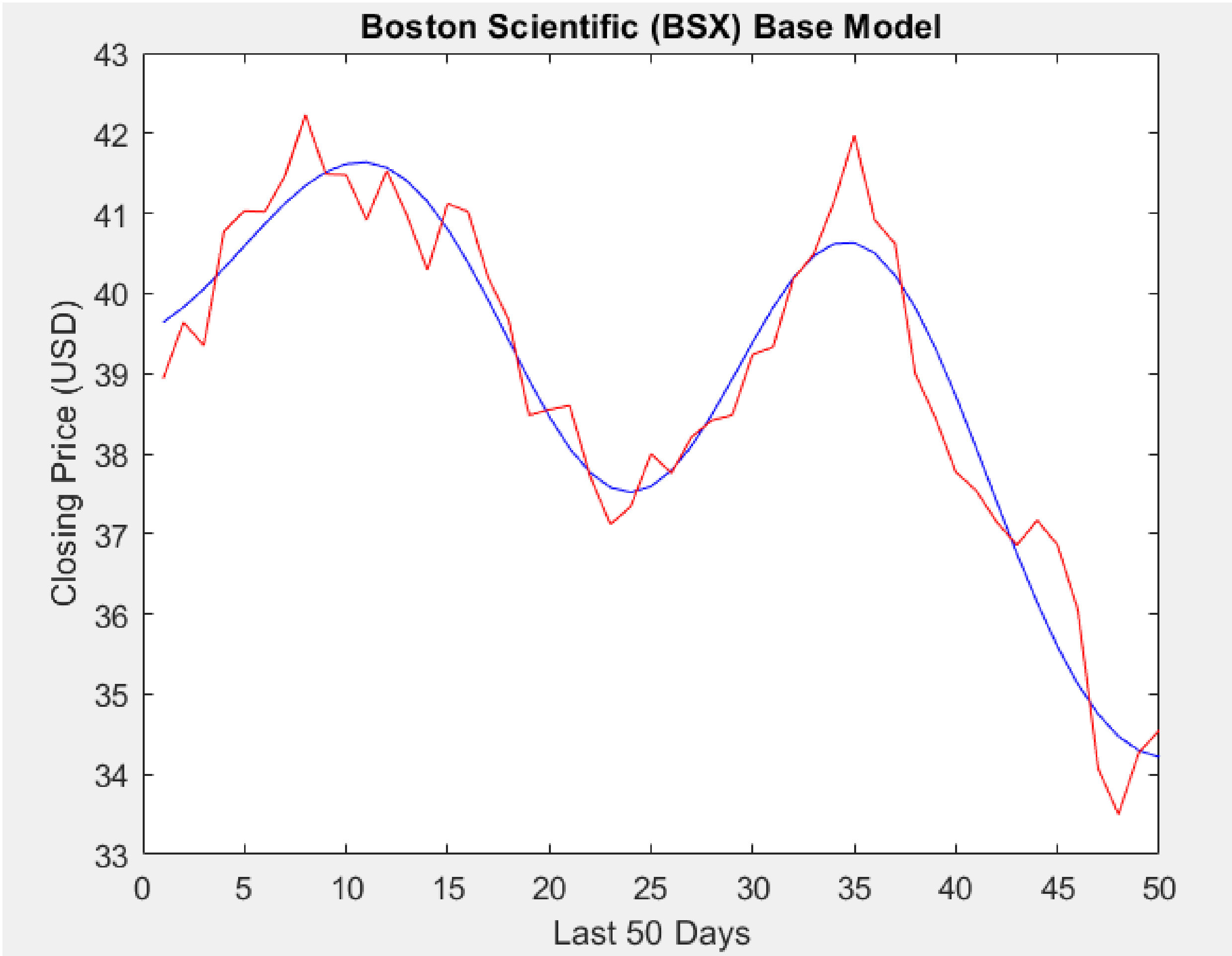

Boston Scientific (BSX) Closing Prices
Closing Price (USD)
Days Since 11/5/2018
50
45
40
35
30
25
0
100
200
300
400
500
600

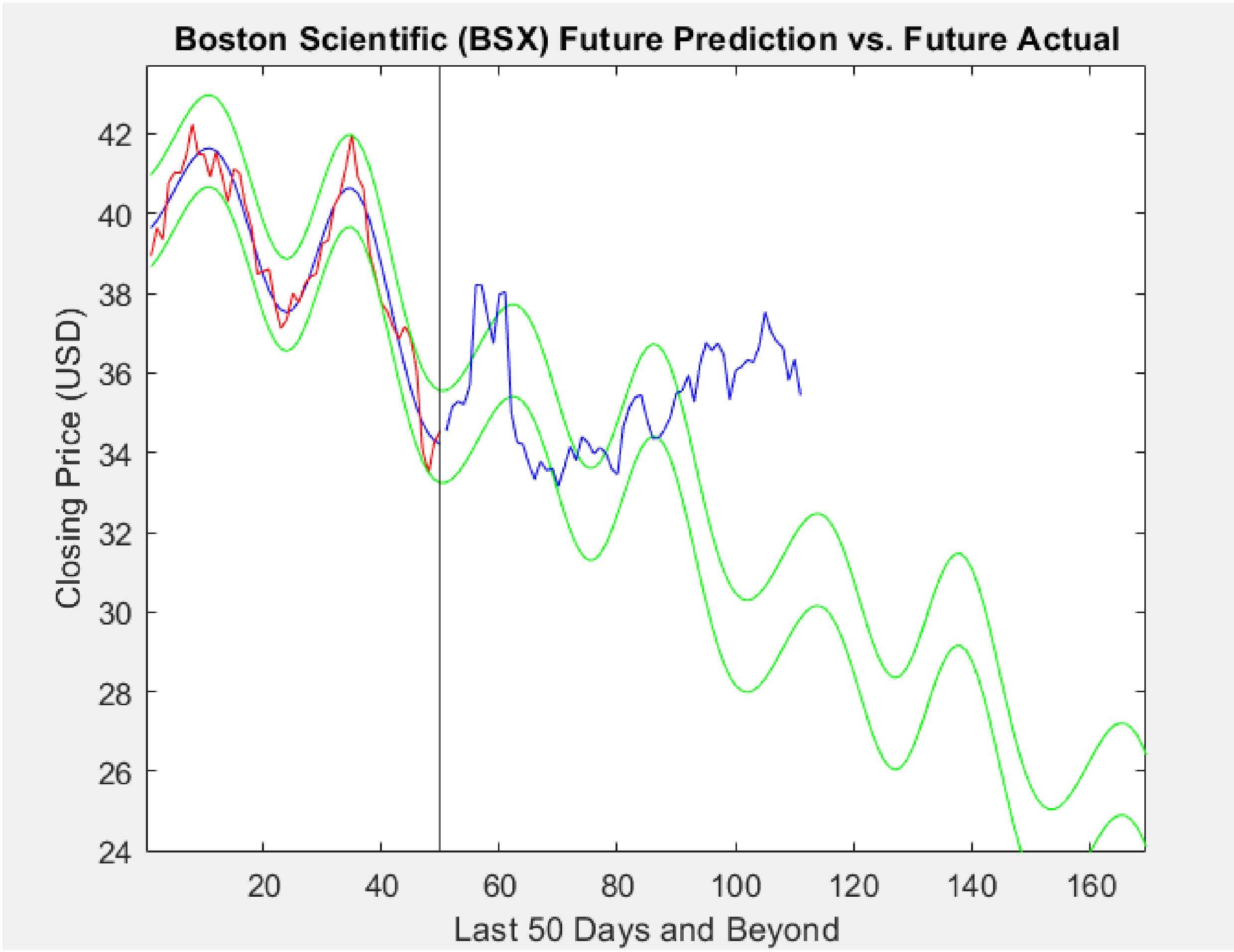

Boston Scientific (BSX) Autocorrelation
Autocorrelation
Lag
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
100
200
300
400
500
600

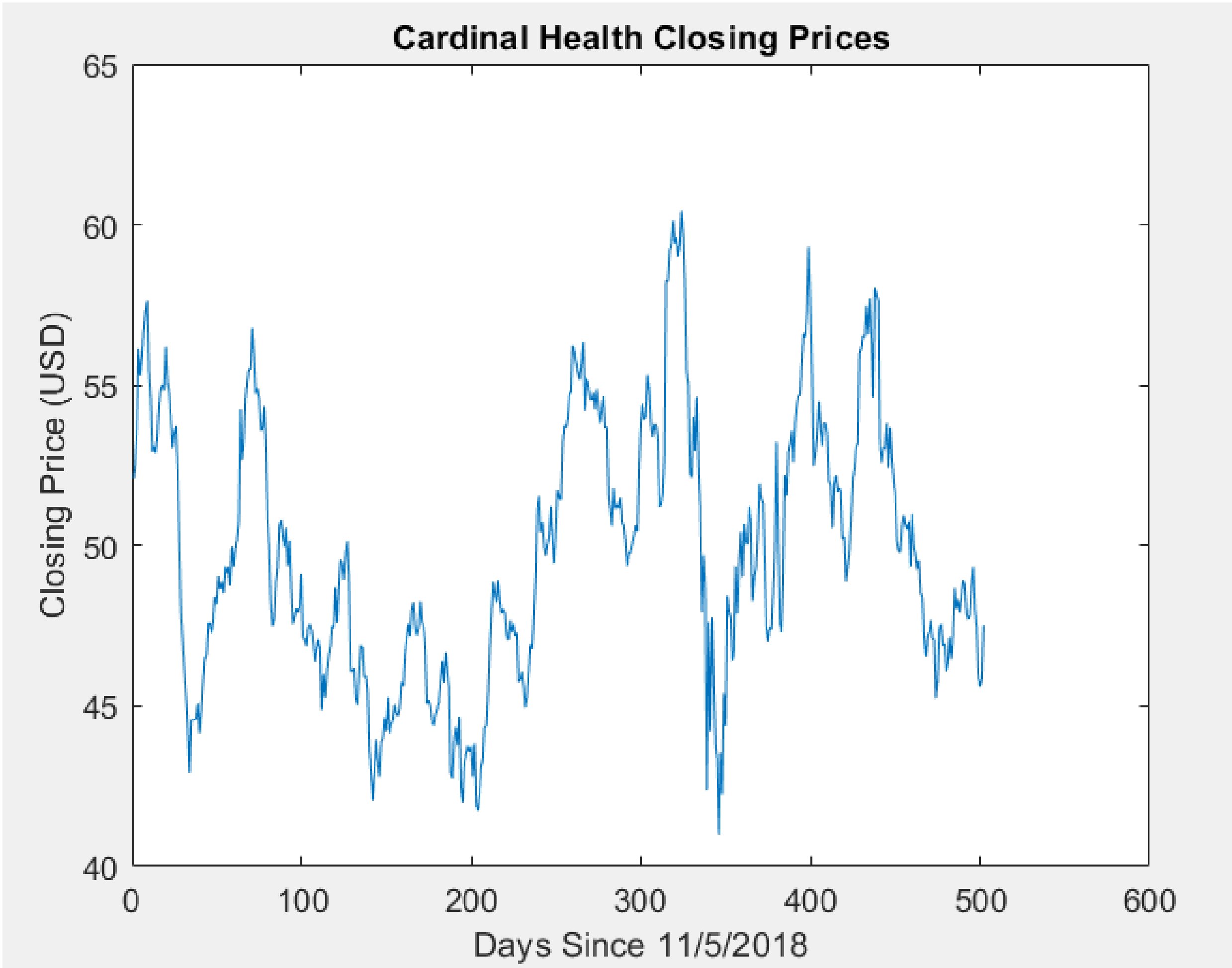

Boston Scientific (BSX) Relevant Period
Closing Price (USD)
43
42
41
40
39
38
37
36
35
34
33
0
5
10
15
20
25
30
35
40
45
50
Last 50 Days

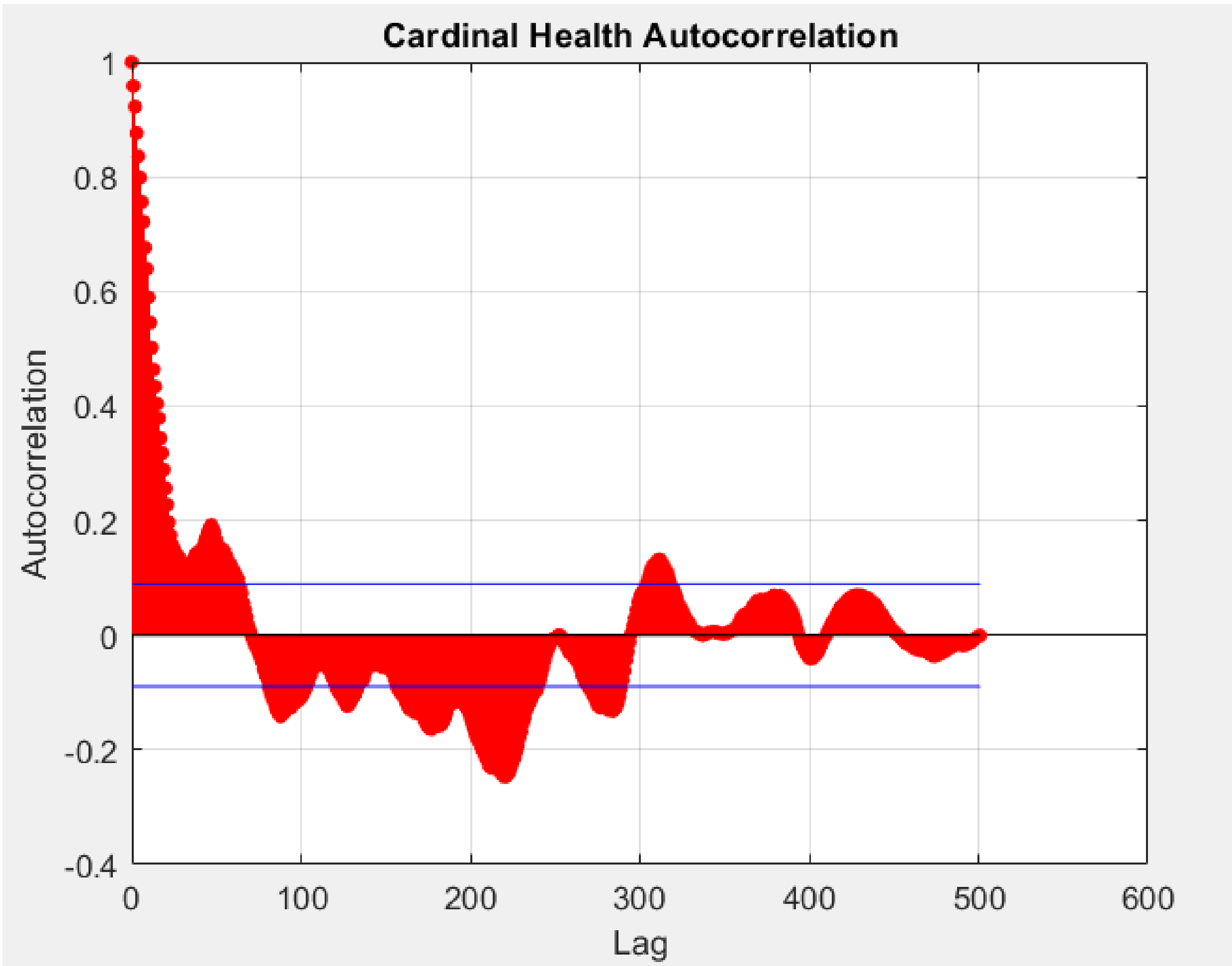

Boston Scientific (BSX) Closing Price /w Trendline
Closing Price (USD)
Last 50 Days
43
42
41
40
39
38
37
36
35
34
33
0
5
10
15
20
25
30
35
40
45
50

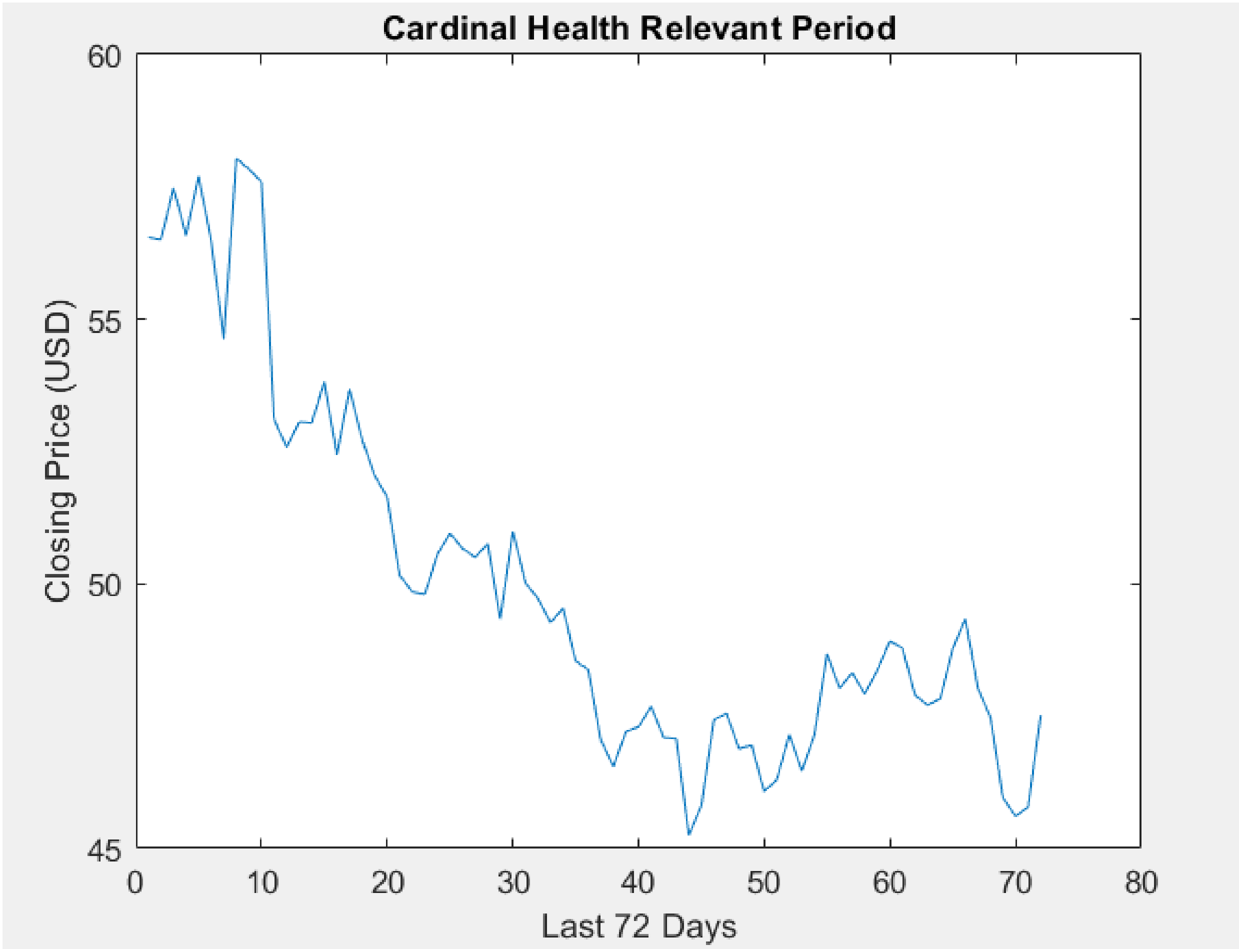

Boston Scientific (BSX) Trendline Residuals
Residual (USD)
4
3
2
1
0
-1
-2
-3
-4
0
5
10
15
20
25
30
35
40
45
50
Last 50 Days


Boston Scientific (BSX) Base Model
Closing Price (USD)
Last 50 Days
43
42
41
40
39
38
37
36
35
34
33
0
5
10
15
20
25
30
35
40
45
50

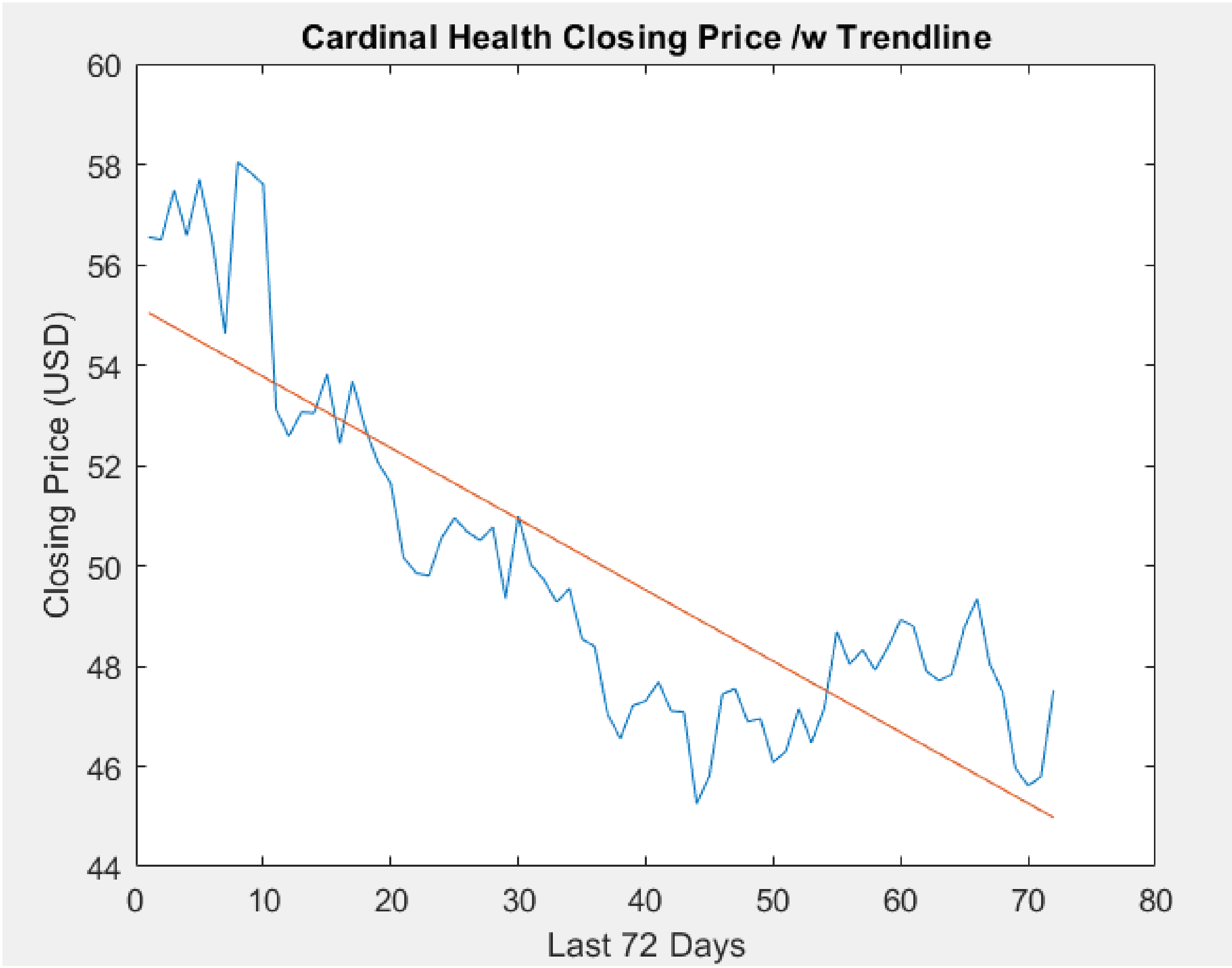

Boston Scientific (BSX) Future Prediction vs. Future Actual
Closing Price (USD)
Last 50 Days and Beyond
42
40
38
36
34
32
30
28
26
24
20
40
60
80
100
120
140
160

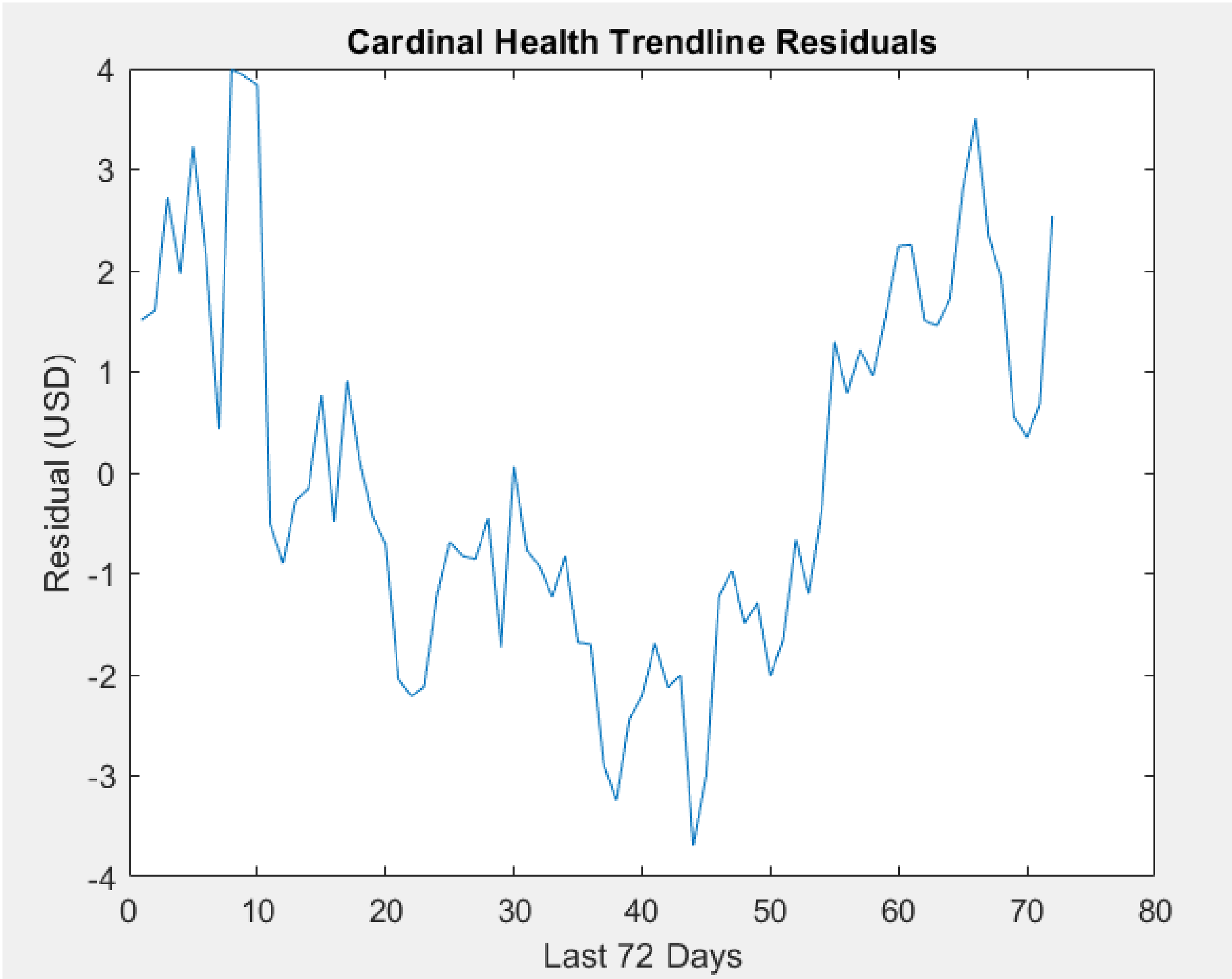

Cardinal Health Closing Prices
Closing Price (USD)
65
60
55
50
45
40
0
100
200
300
400
500
600
Days Since 11/5/2018

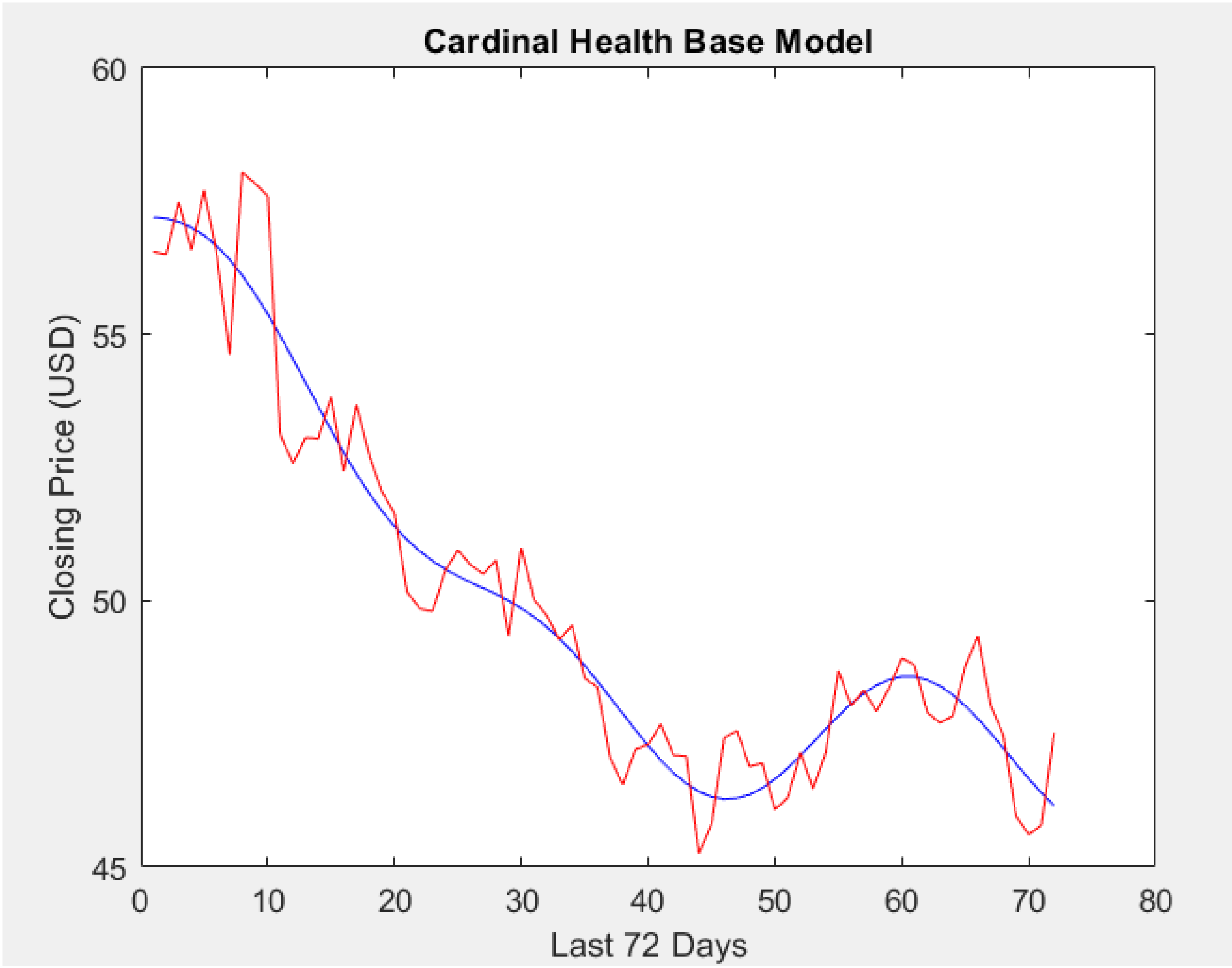

Cardinal Health Autocorrelation
Autocorrelation
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
100
200
300
400
500
600
Lag

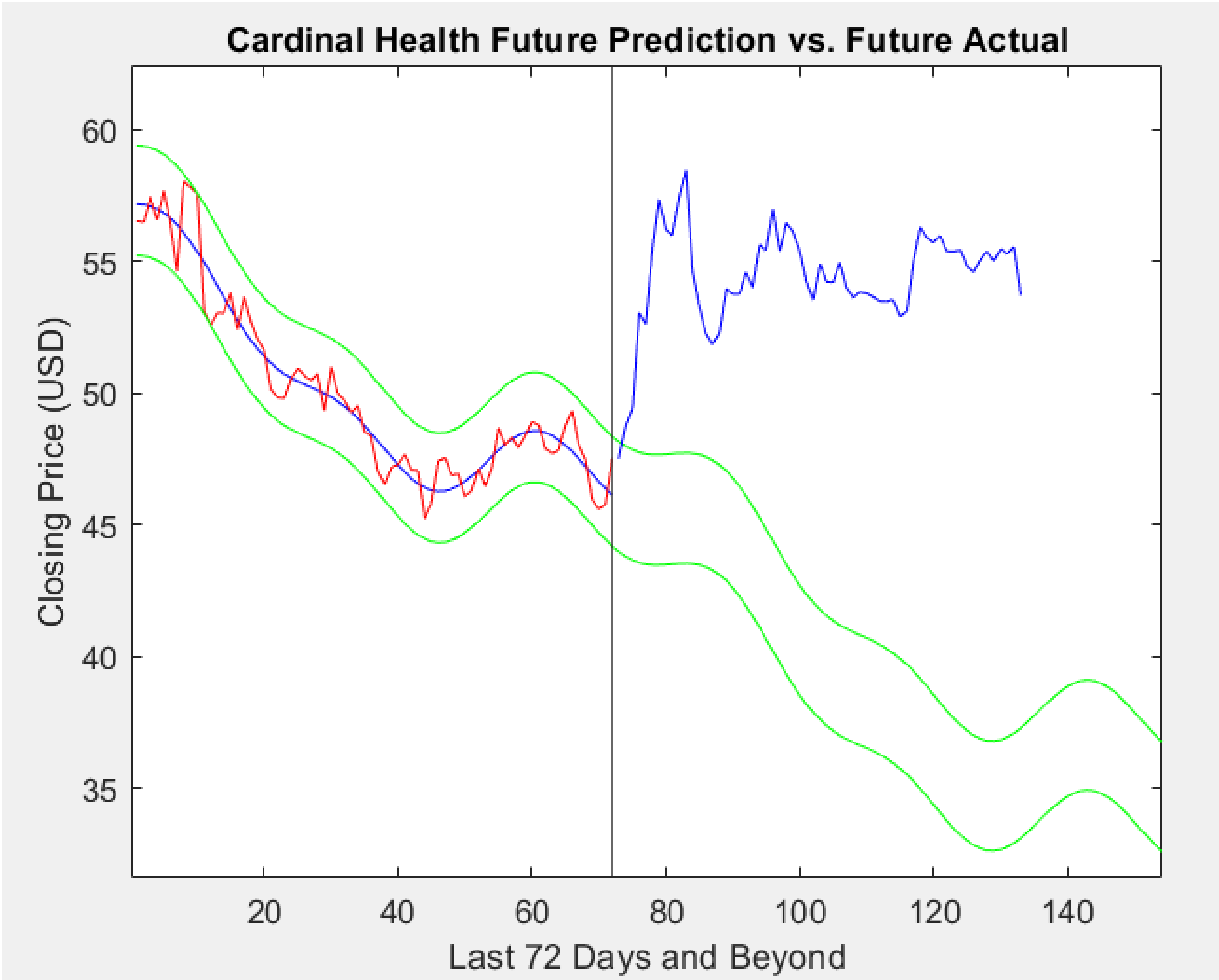


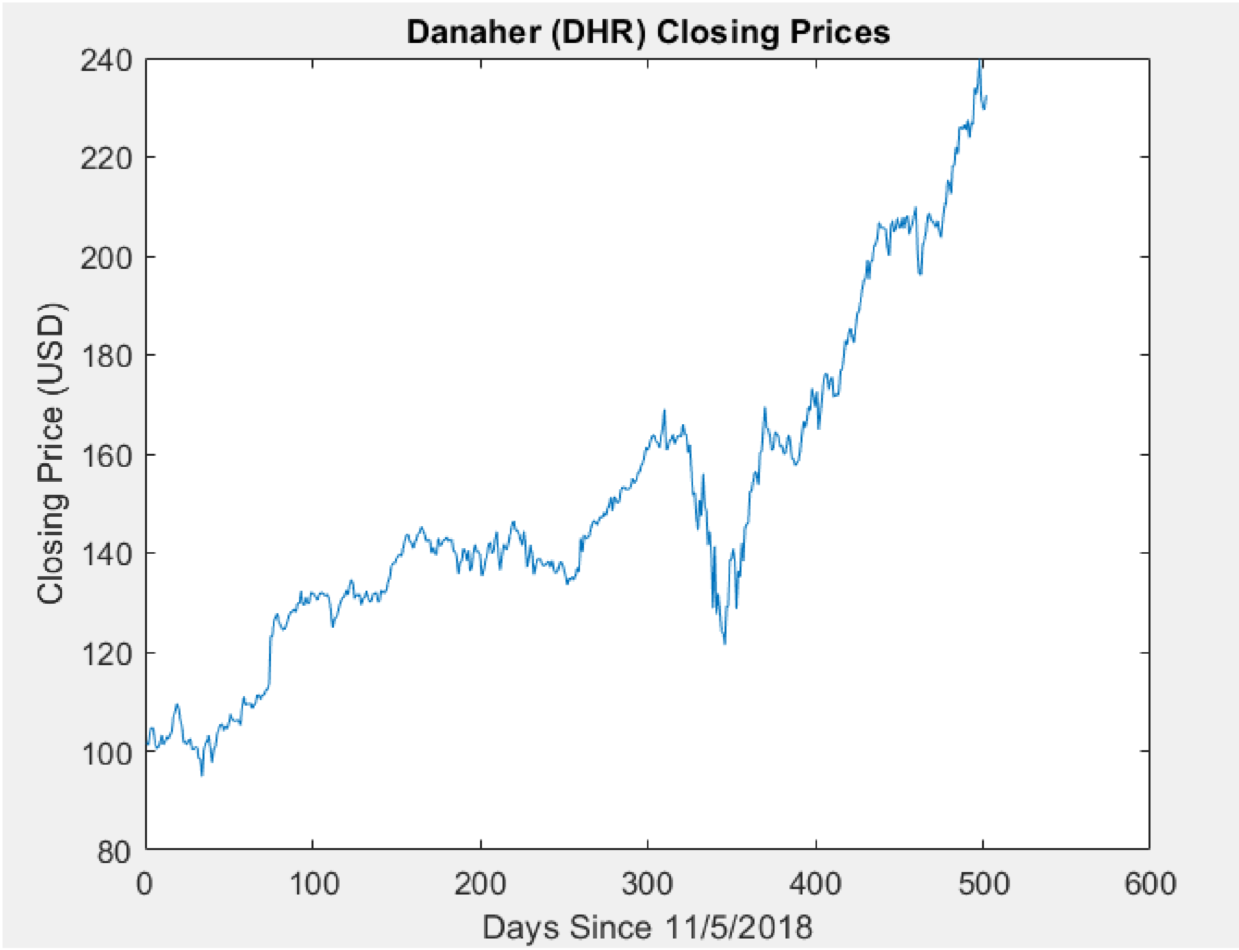
Cardinal Health Relevant Period
Closing Price (USD)
Last 72 Days
60
55
50
45
0
10
20
30
40
50
60
70
80

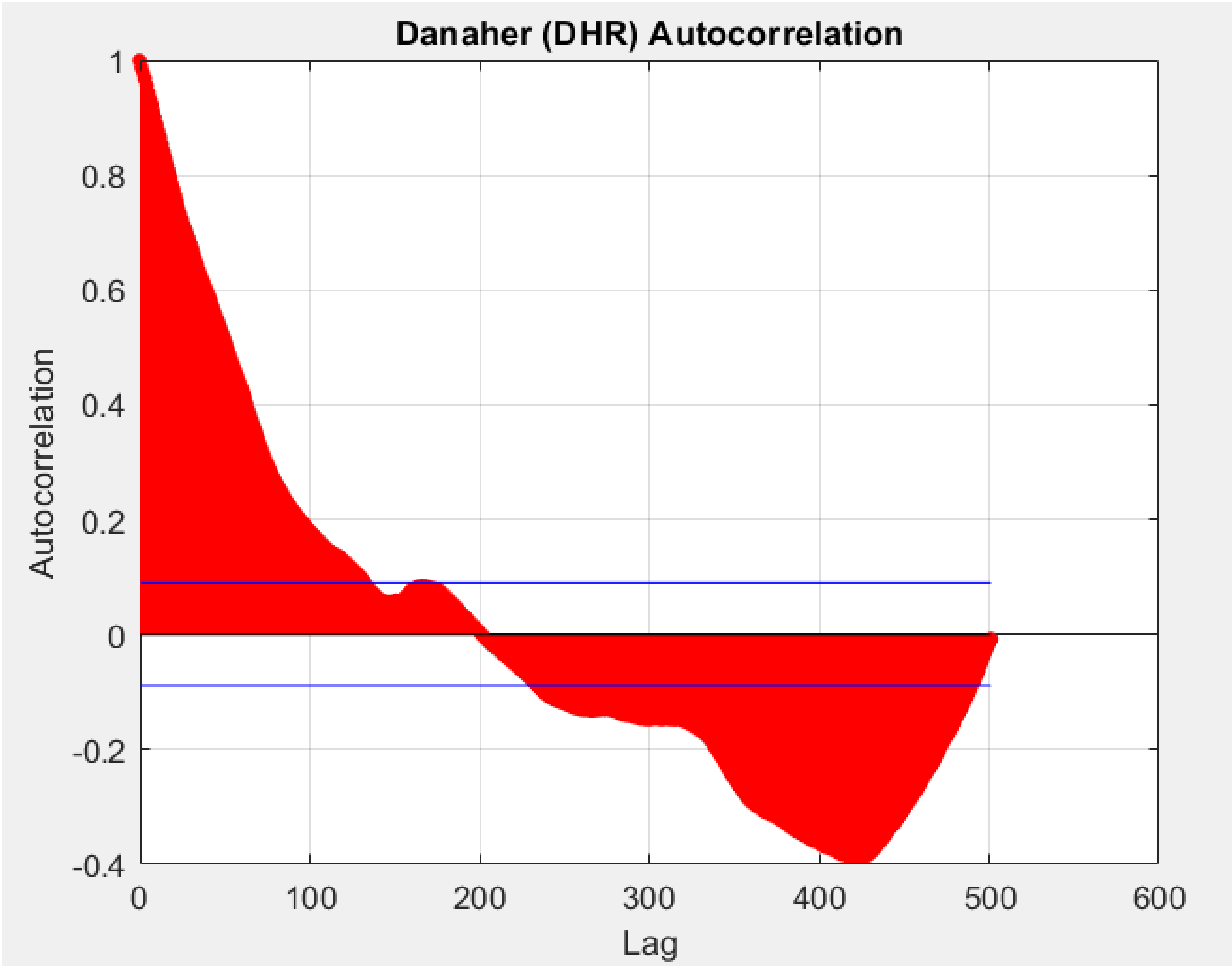

Cardinal Health Closing Price /w Trendline
Closing Price (USD)
60
58
56
54
52
50
48
46
44
0
10
20
30
40
50
60
70
80
Last 72 Days


Cardinal Health Trendline Residuals
Residual (USD)
Last 72 Days
4
3
2
1
0
-1
-2
-3
-4
0
10
20
30
40
50
60
70
80

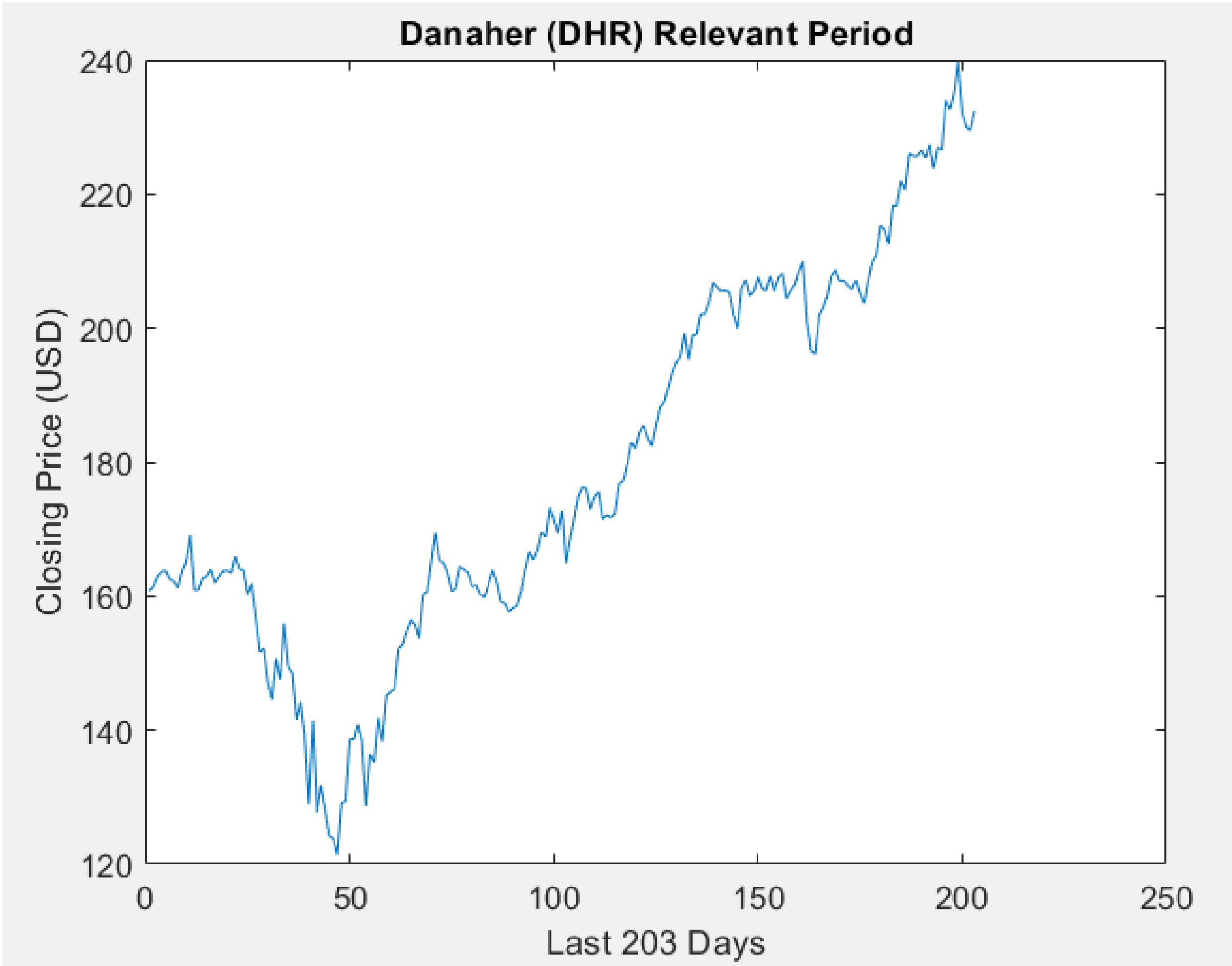

Cardinal Health Base Model
Closing Price (USD)
Last 72 Days
60
55
50
45
0
10
20
30
40
50
60
70
80

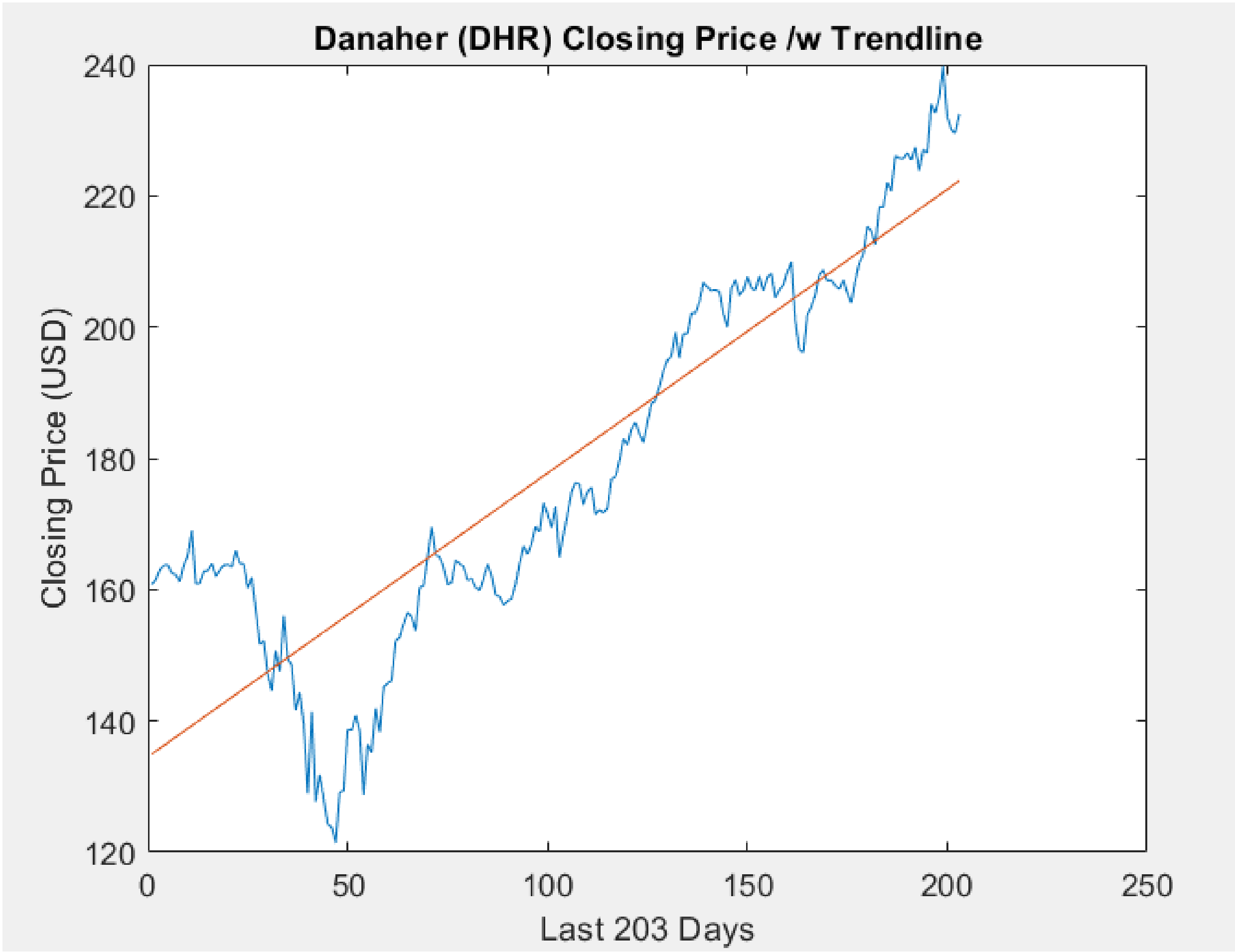

Cardinal Health Future Prediction vs. Future Actual
Closing Price (USD)
60
55
50
45
40
35
20
40
60
80
100
120
140
Last 72 Days and Beyond

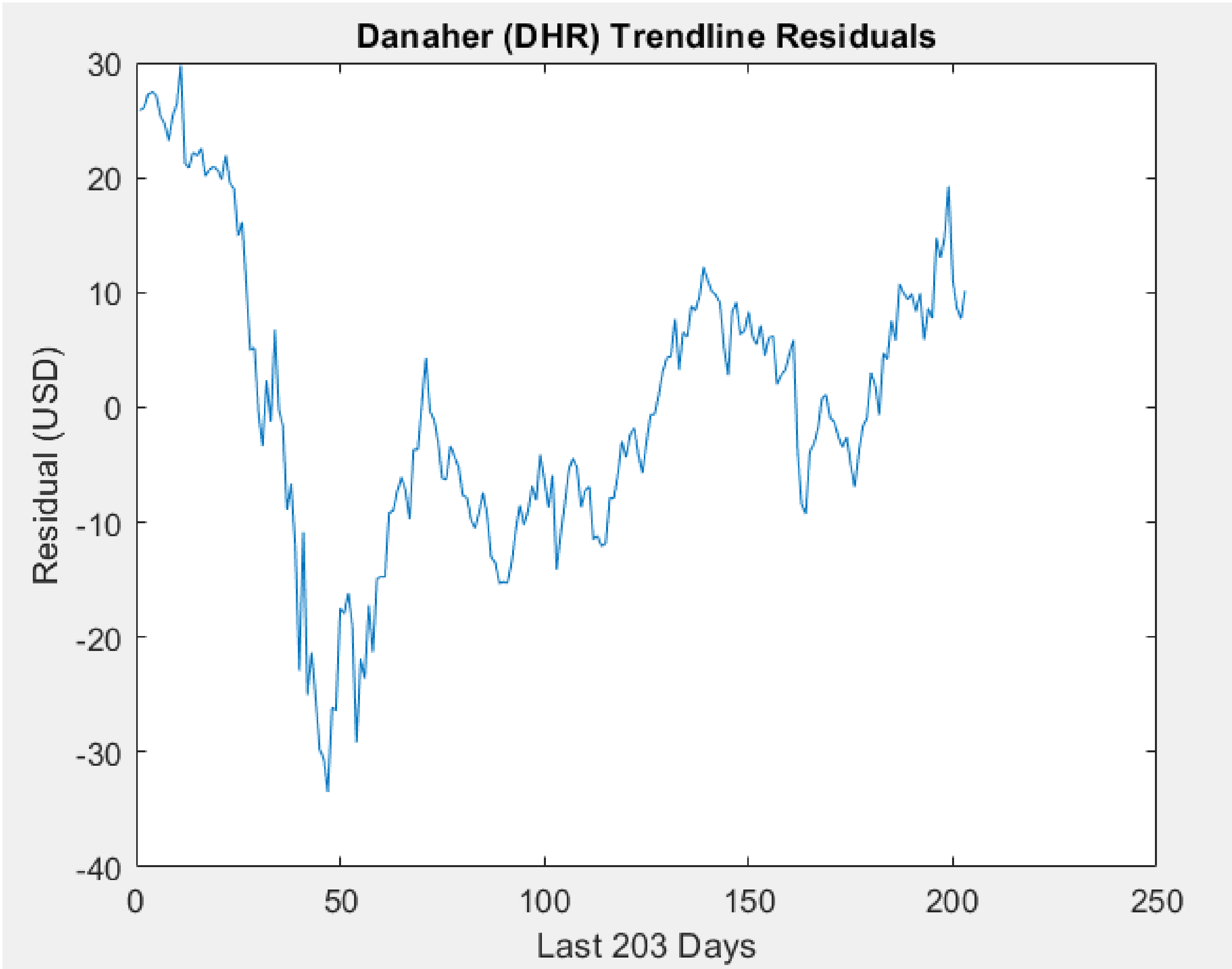

Danaher (DHR) Closing Prices
Closing Price (USD)
240
220
200
180
160
140
120
100
80
0
100
200
300
400
500
600
Days Since 11/5/2018

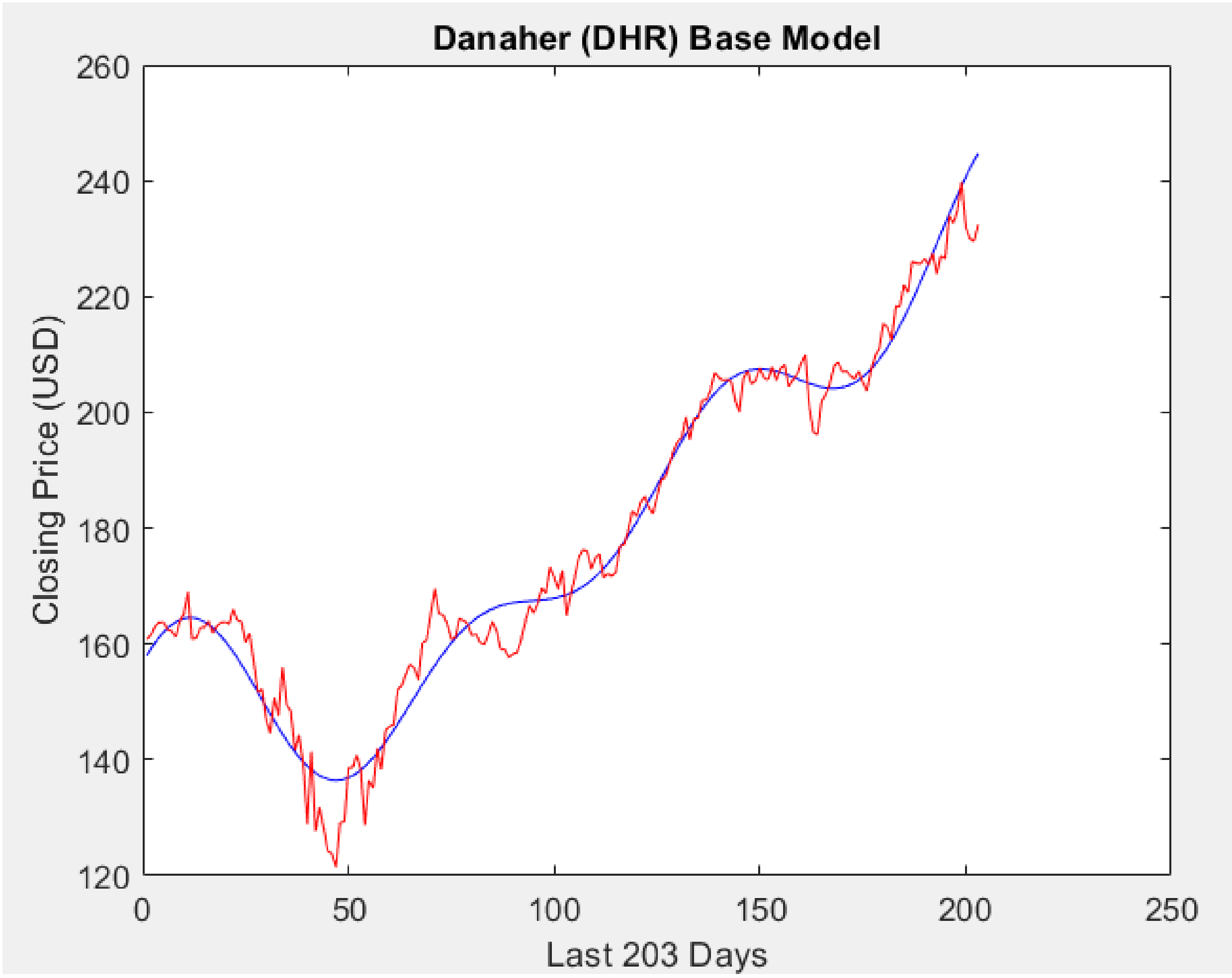


Danaher (DHR) Autocorrelation
Autocorrelation
Lag
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
100
200
300
400
500
600

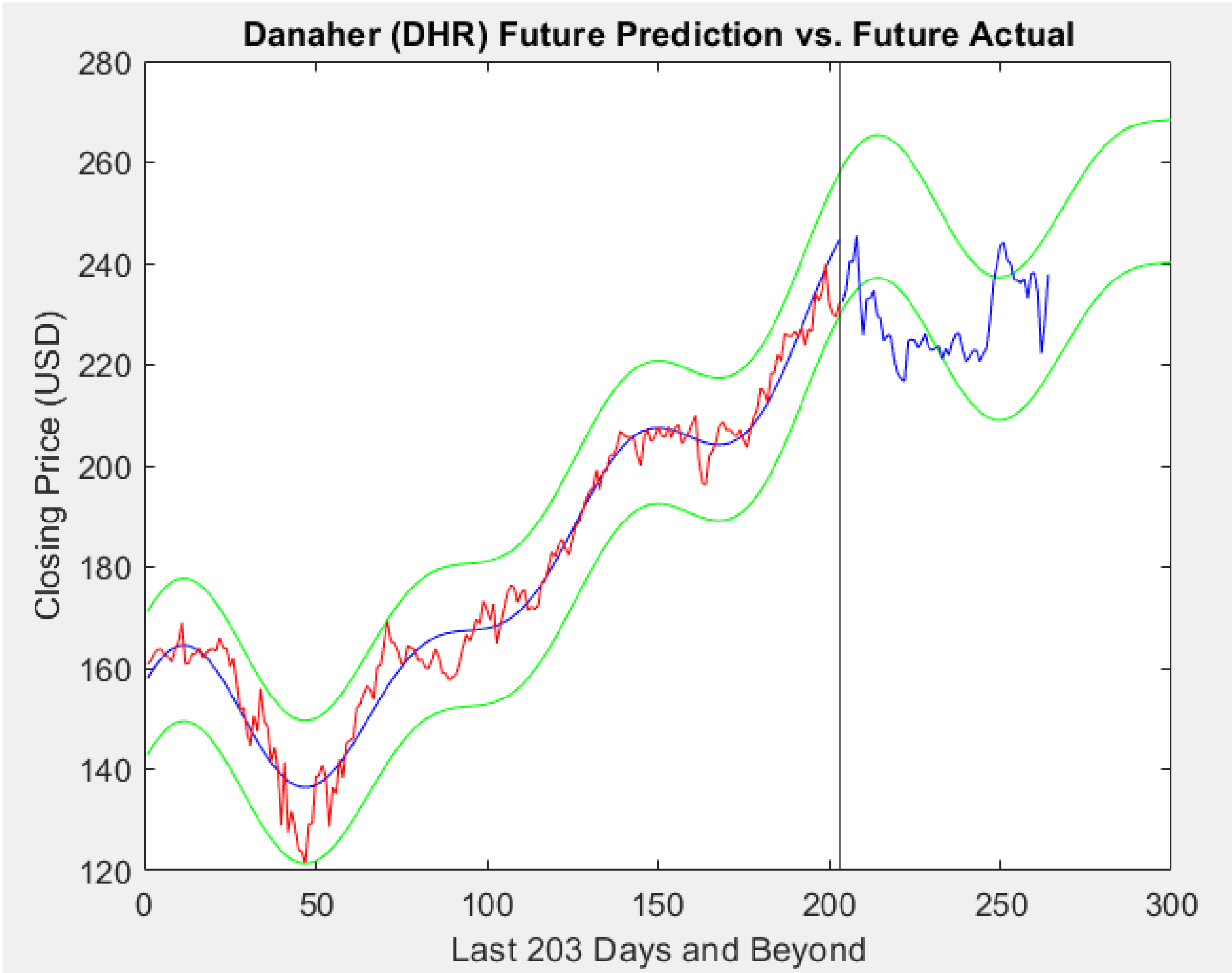

Danaher (DHR) Relevant Period
240
220
200
180
160
140
120
Closing Price (USD)
0
50
100
150
200
250
Last 203 Days

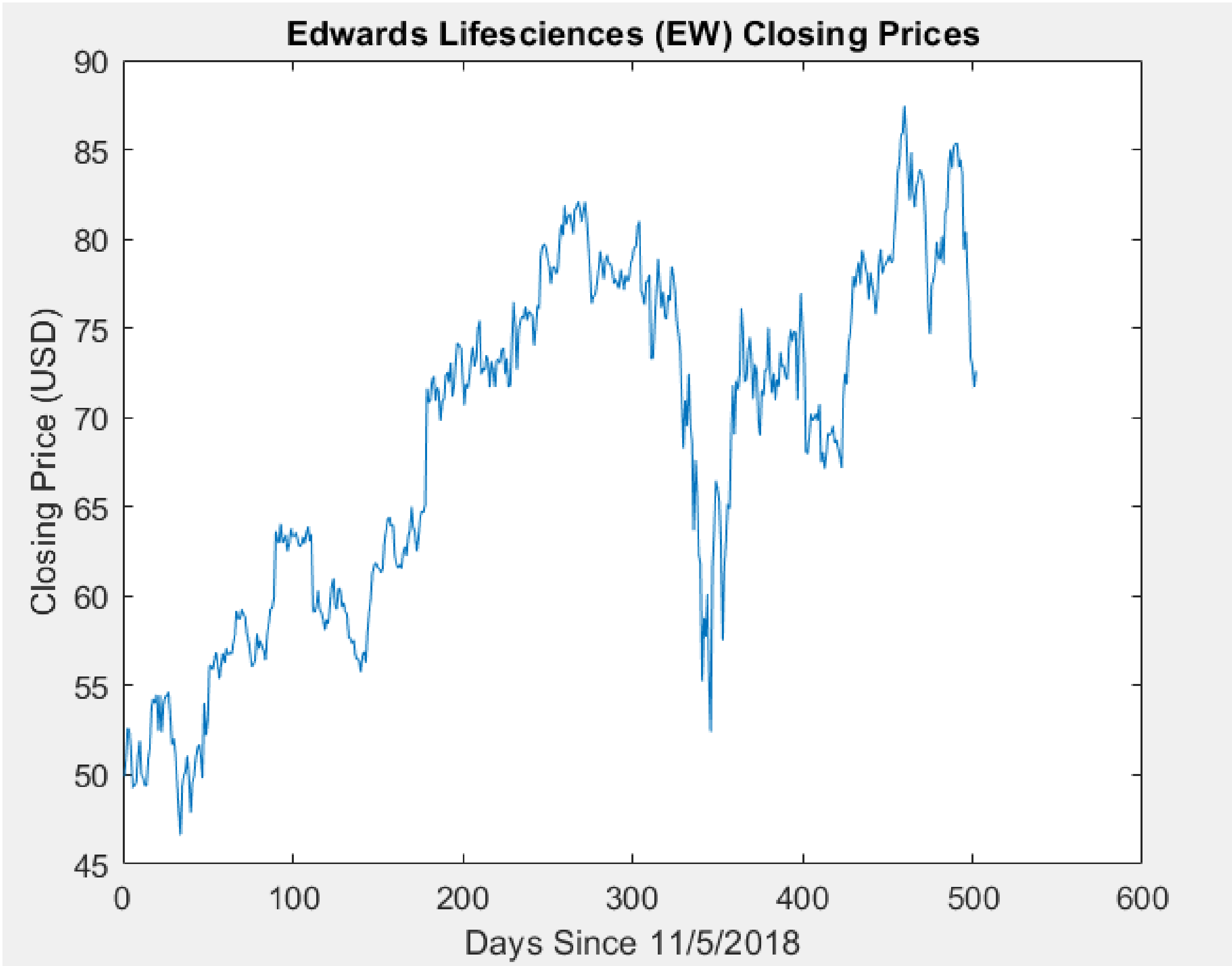

Danaher (DHR) Closing Price /w Trendline
240
220
200
180
160
140
120
Closing Price (USD)
0
50
100
150
200
250
Last 203 Days

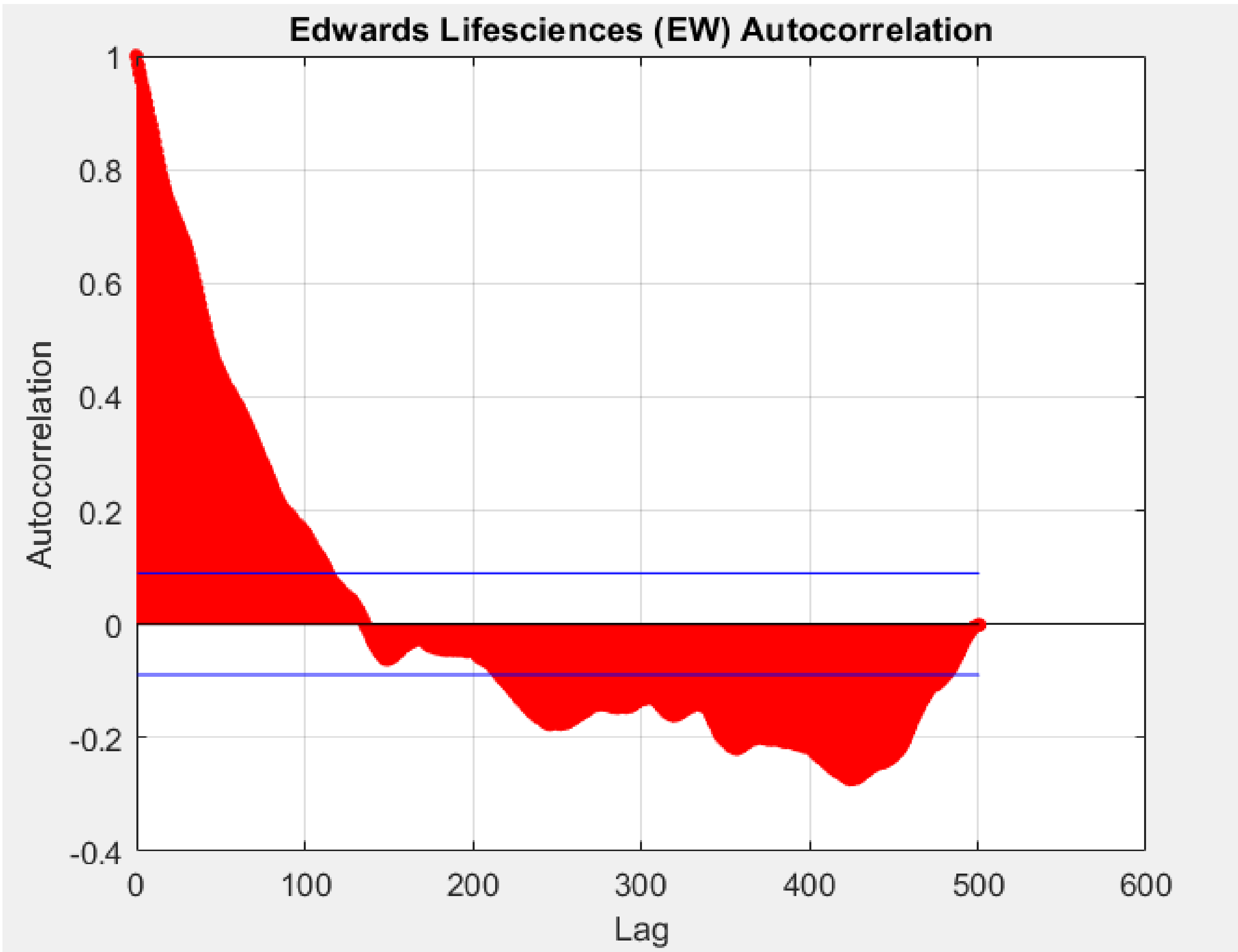

Danaher (DHR) Trendline Residuals
Residual (USD)
30
20
10
0
-10
-20
-30
-40
0
50
100
150
200
250
Last 203 Days

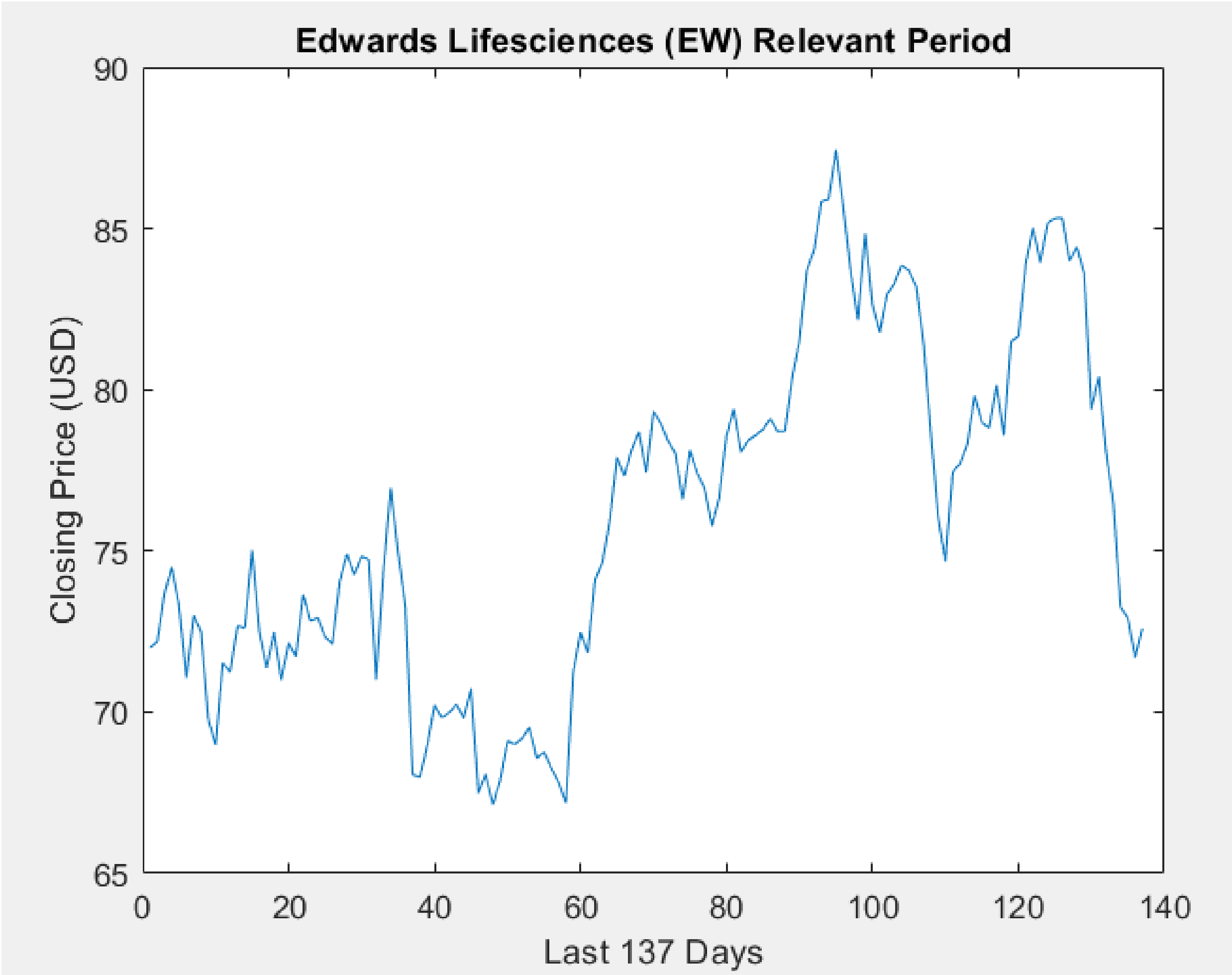


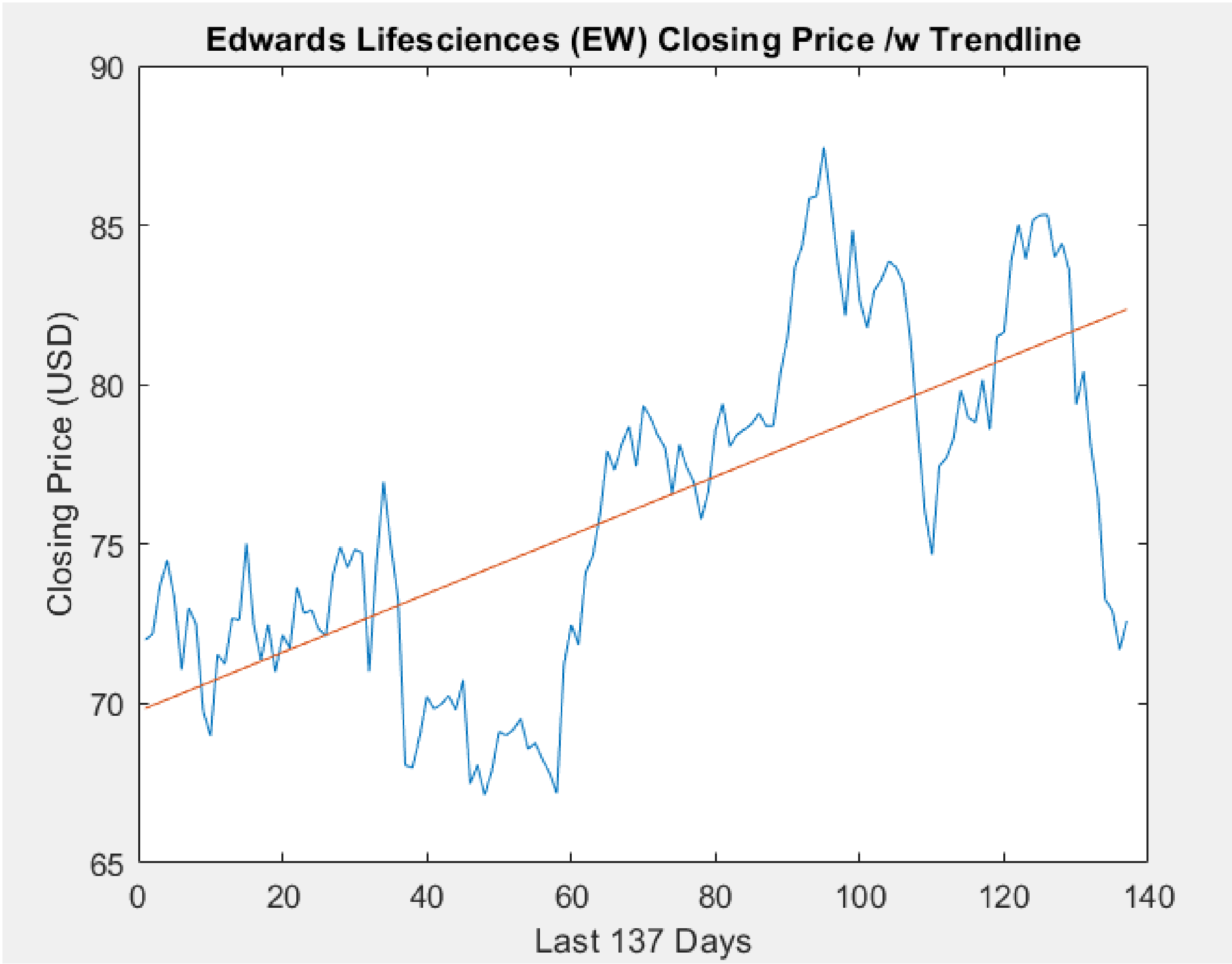
Danaher (DHR) Base Model
Closing Price (USD)
260
240
220
200
180
160
140
120
0
50
100
150
200
250
Last 203 Days


Danaher (DHR) Future Prediction vs. Future Actual
280
260
240
220
200
180
160
140
120
Closing Price (USD)
0
50
100
150
200
250
300
Last 203 Days and Beyond

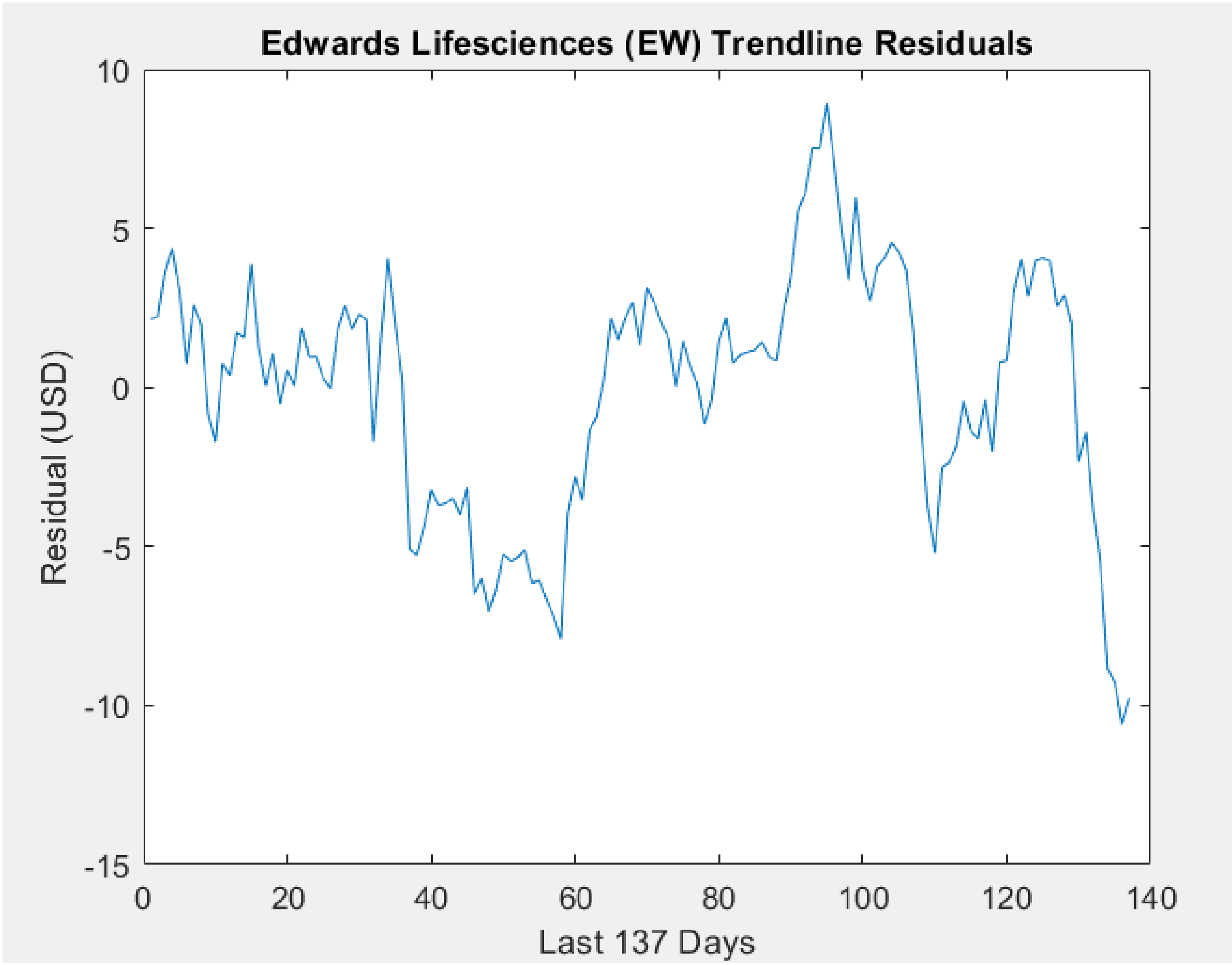

Edwards Lifesciences (EW) Closing Prices
Closing Price (USD)
Days Since 11/5/2018
90
85
80
75
70
65
60
55
50
45
0
100
200
300
400
500
600

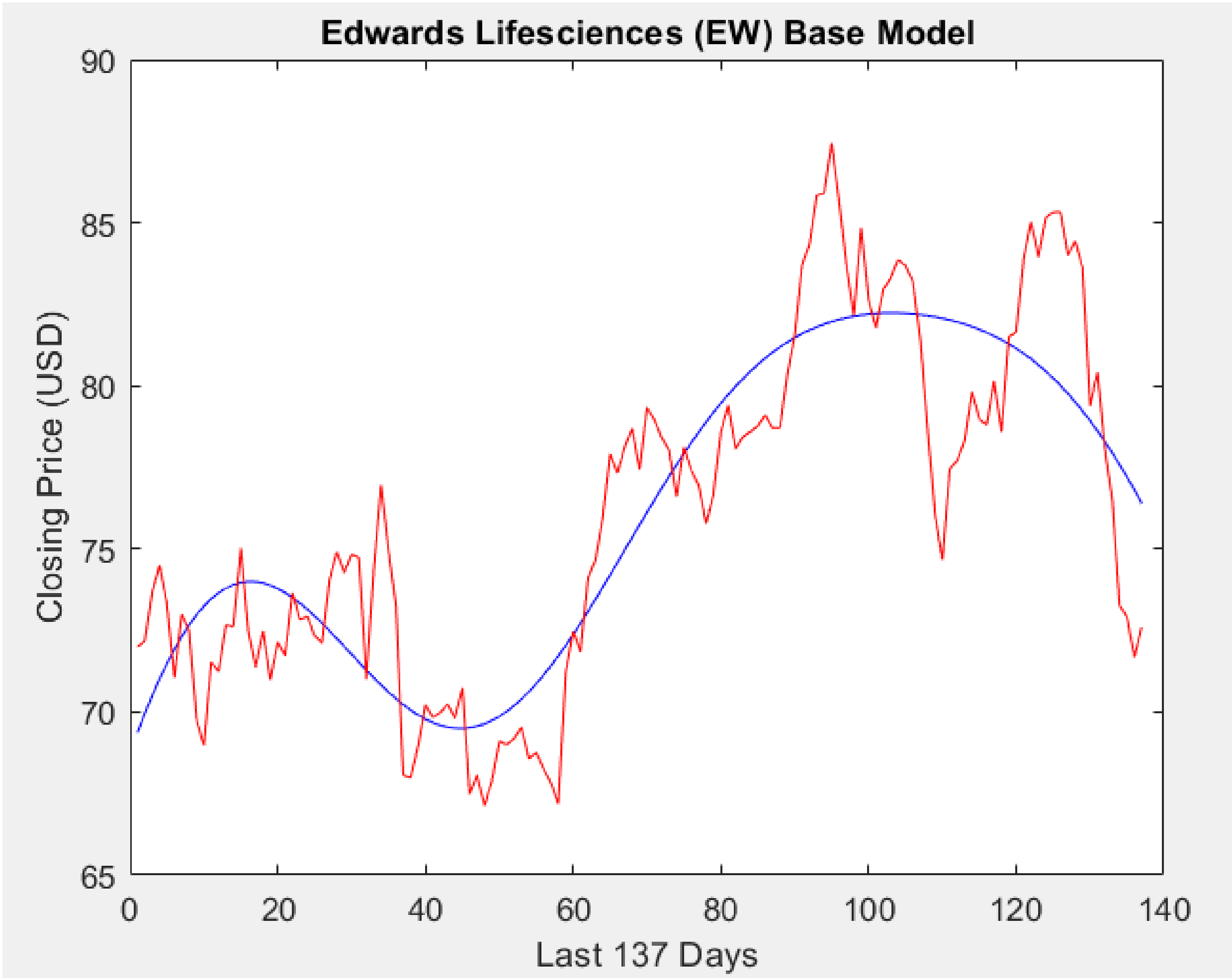

Edwards Lifesciences (EW) Autocorrelation
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
Autocorrelation
0
100
200
300
400
500
600
Lag


Edwards Lifesciences (EW) Relevant Period
Closing Price (USD)
90
85
80
75
70
65
0
20
40
60
80
100
120
140
Last 137 Days

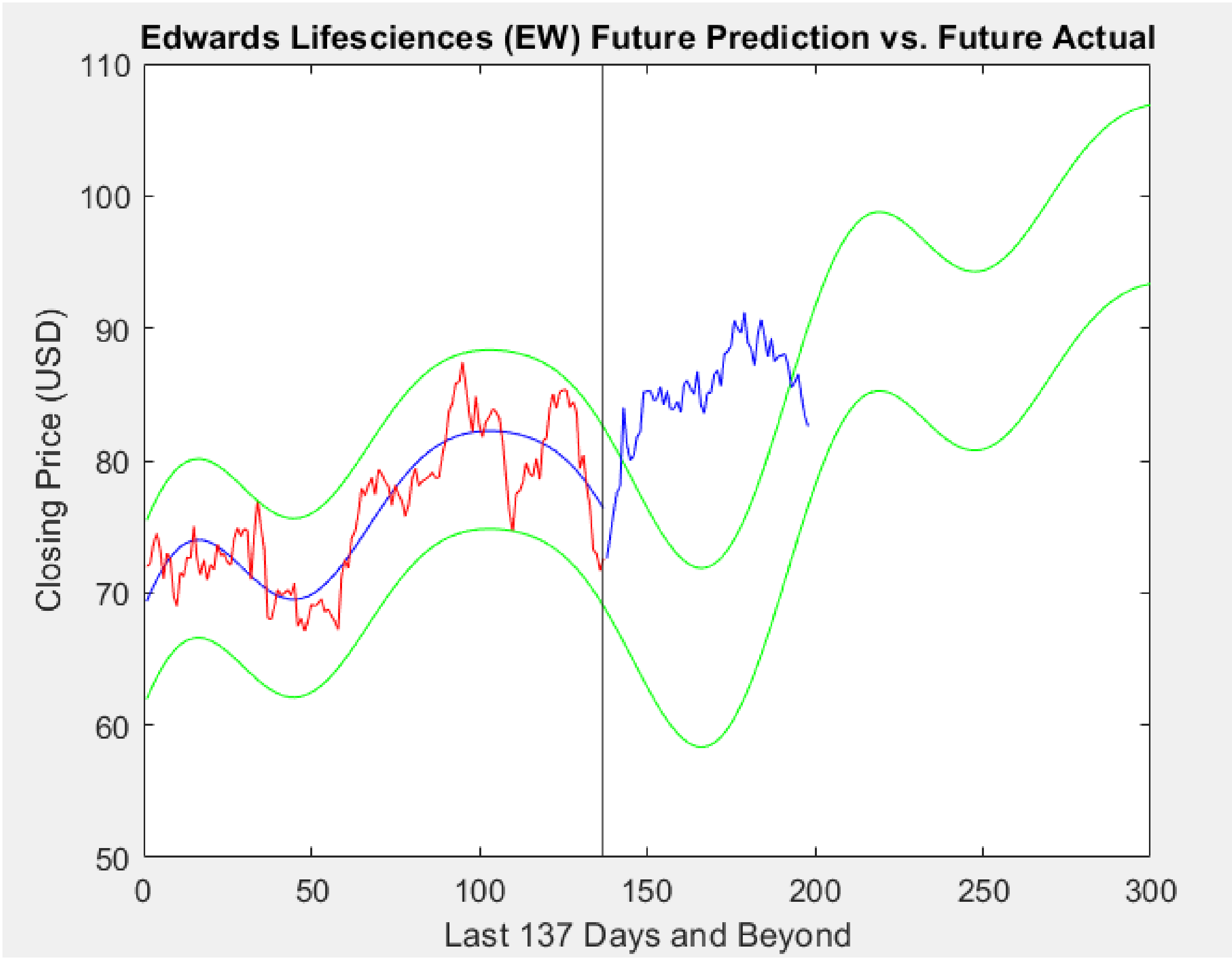


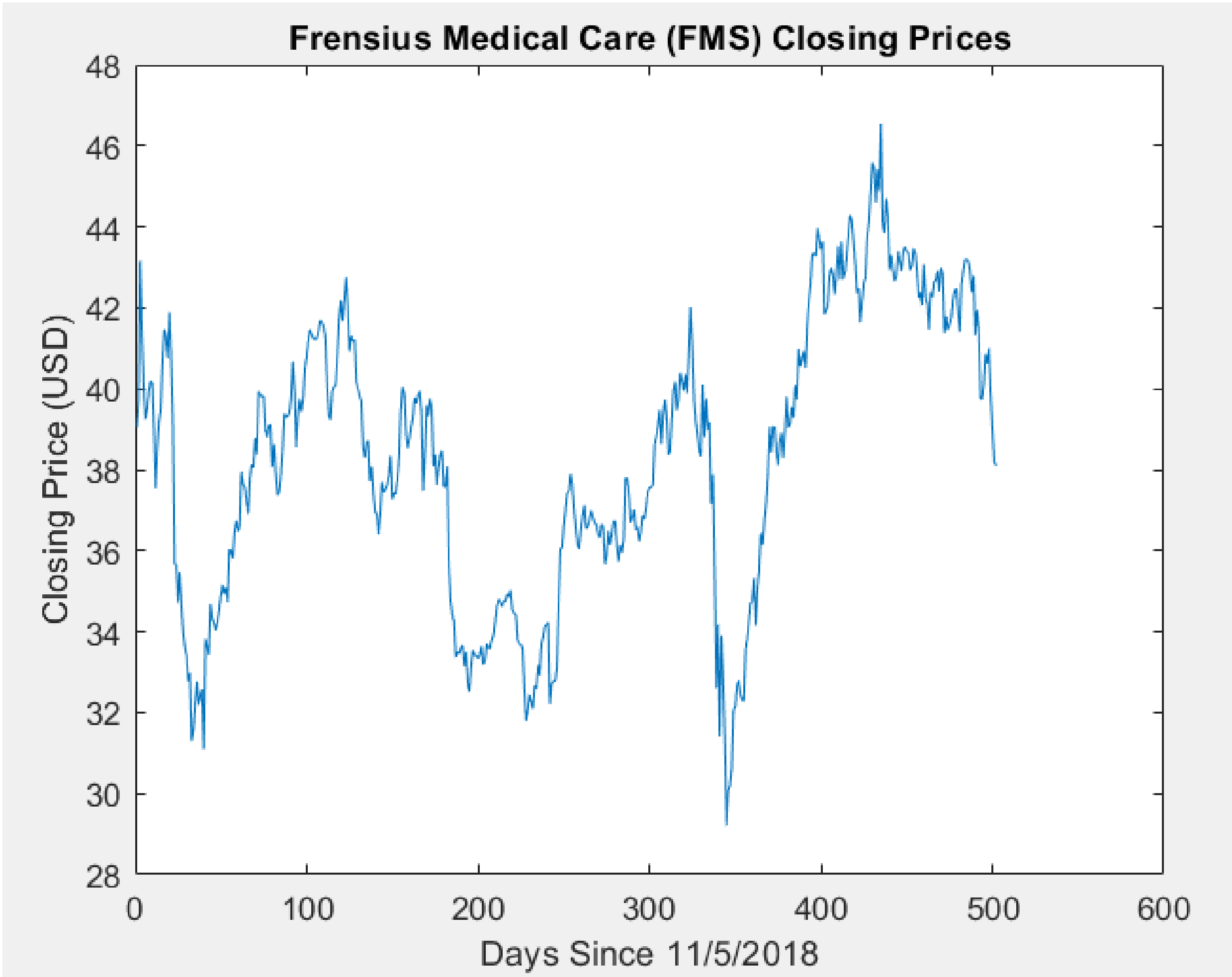
Edwards Lifesciences (EW) Closing Price /w Trendline
90
85
80
75
70
65
Closing Price (USD)
0
20
40
60
80
100
120
140
Last 137 Days


Edwards Lifesciences (EW) Trendline Residuals
Residual (USD)
Last 137 Days
10
5
0
-5
-10
-15
0
20
40
60
80
100
120
140

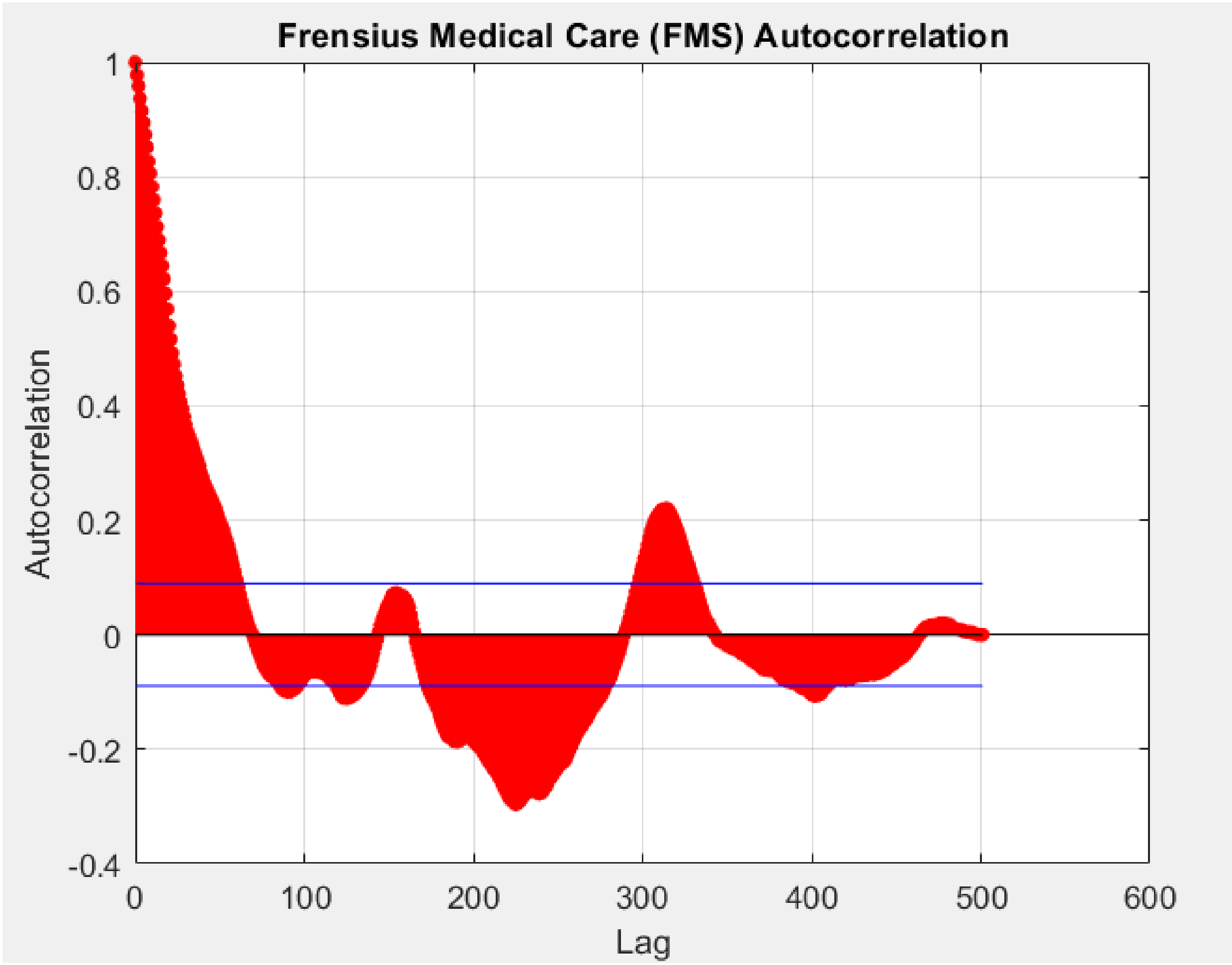


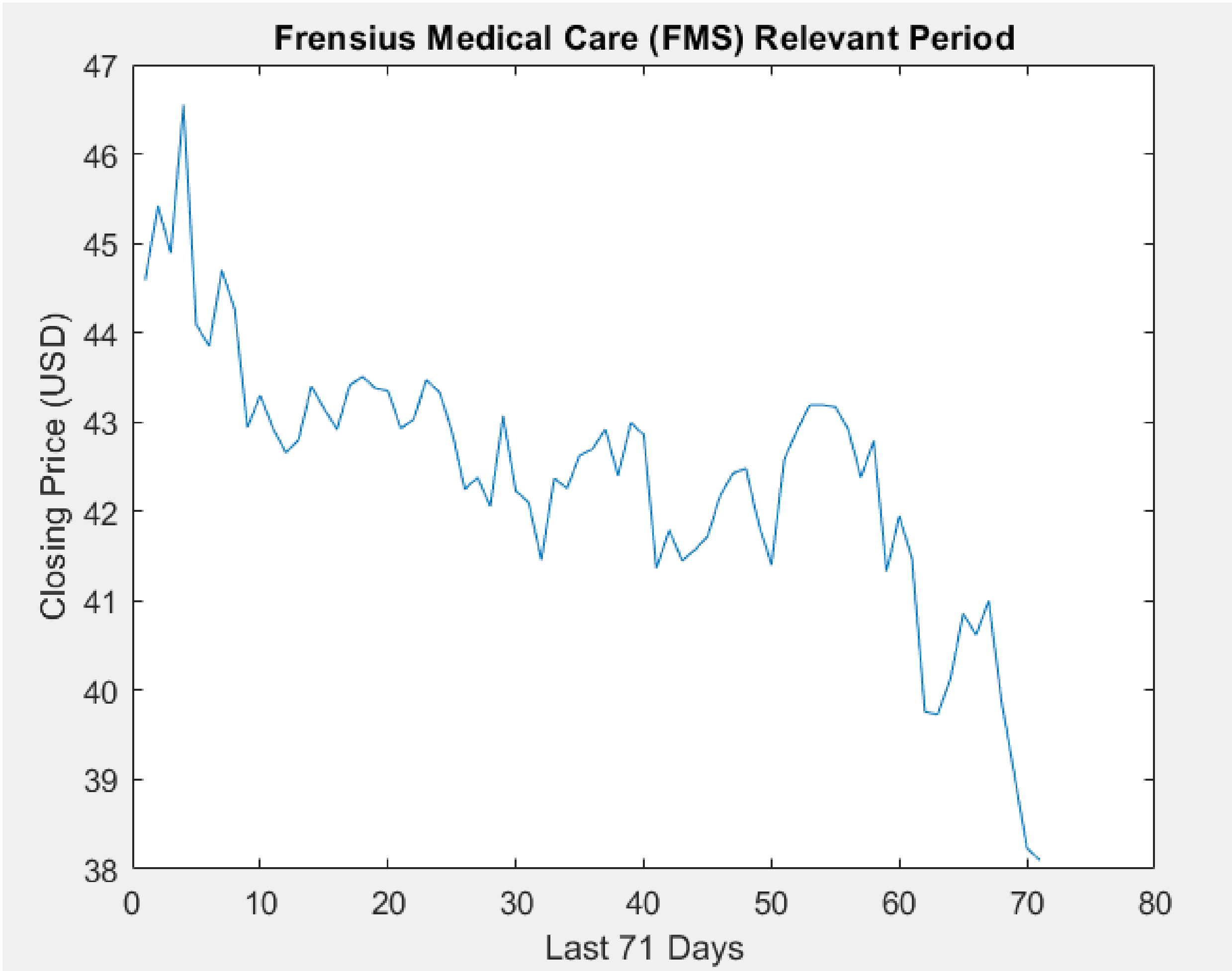
Edwards Lifesciences (EW) Base Model
Closing Price (USD)
Last 137 Days
90
85
80
75
70
65
0
20
40
60
80
100
120
140

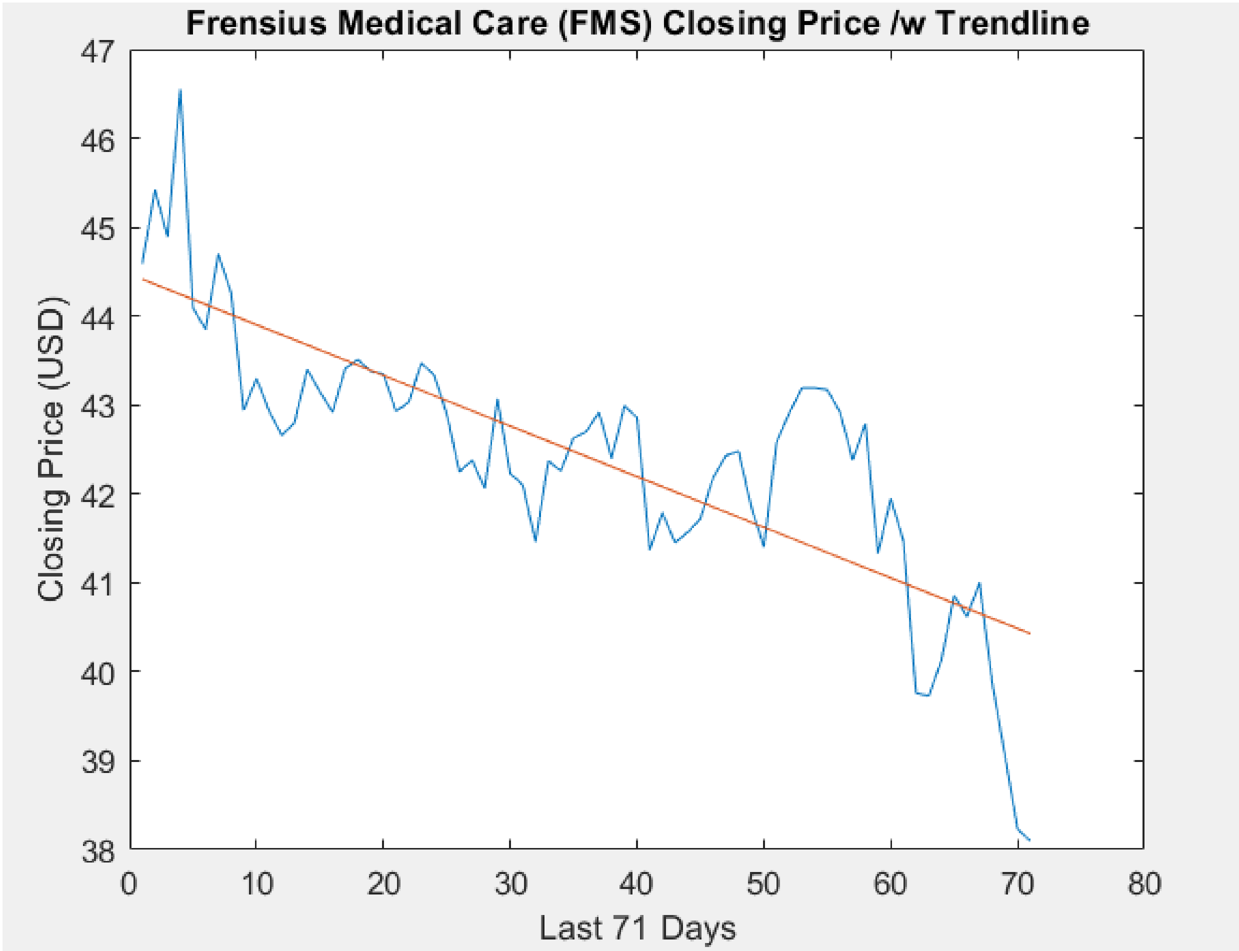

Edwards Lifesciences (EW) Future Prediction vs. Future Actual
Closing Price (USD)
110
100
90
80
70
60
50
0
50
100
150
200
250
300
Last 137 Days and Beyond

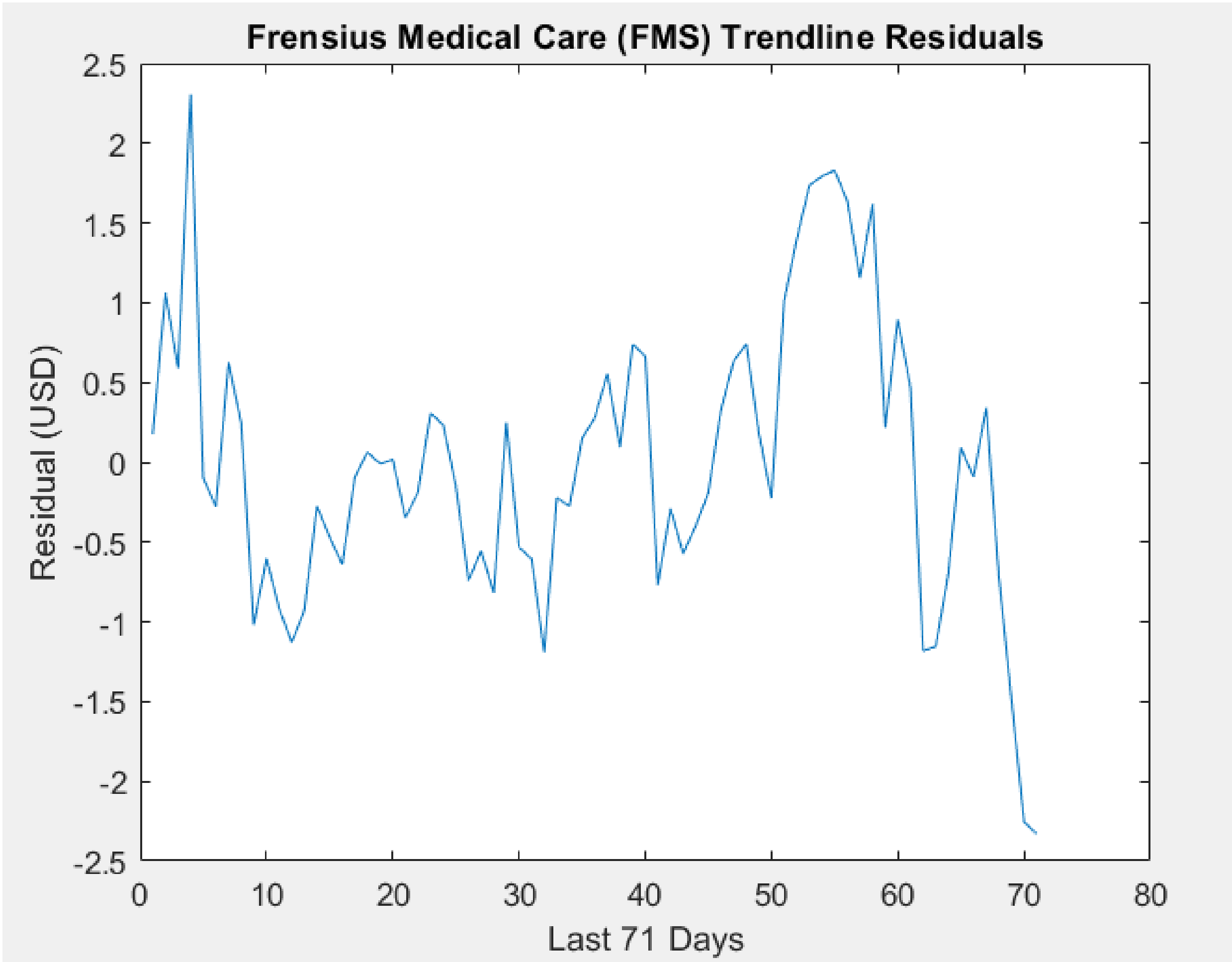


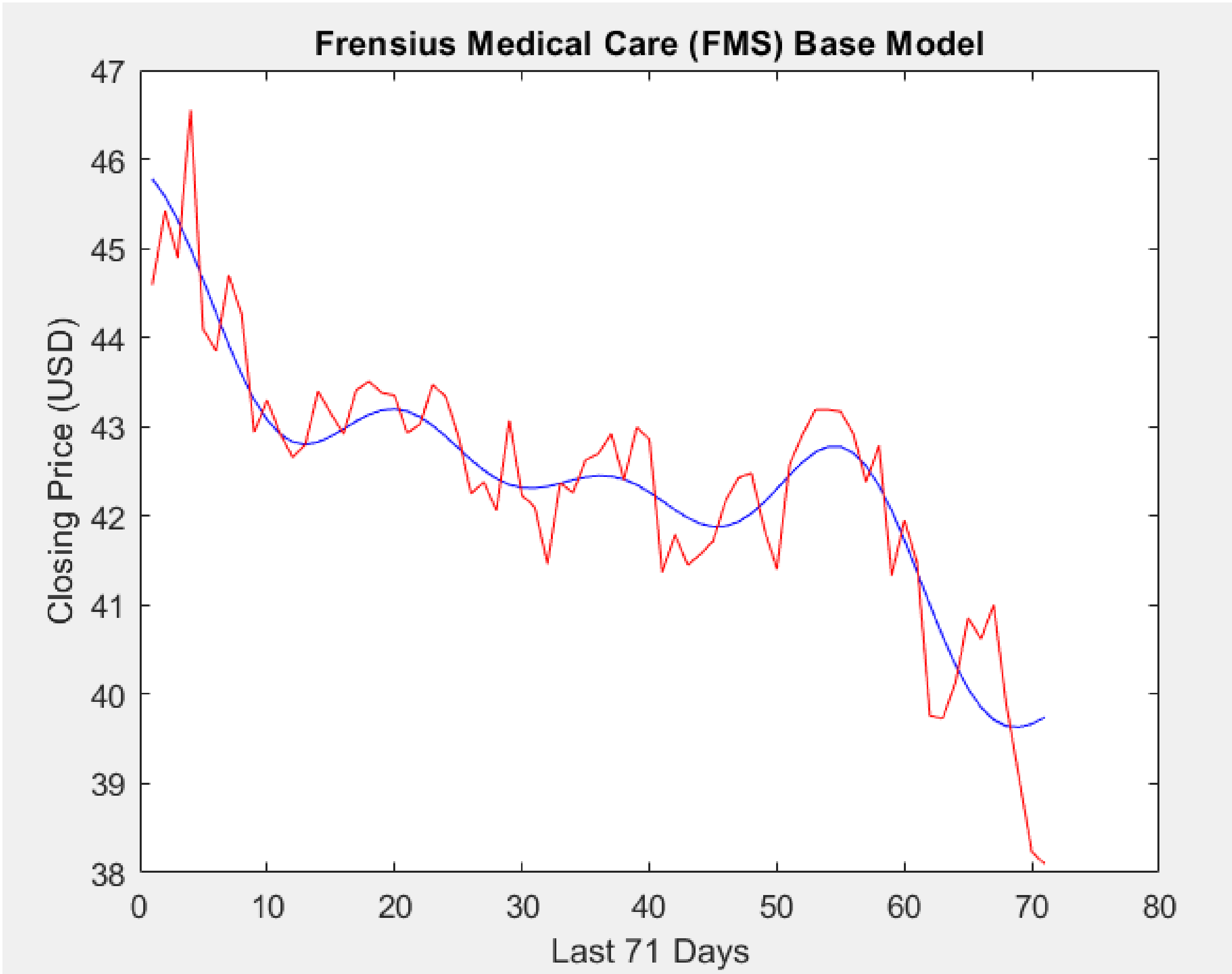
Frensius Medical Care (FMS) Closing Prices
Closing Price (USD)
48
46
44
42
40
38
36
34
32
30
28
0
100
200
300
400
500
600
Days Since 11/5/2018

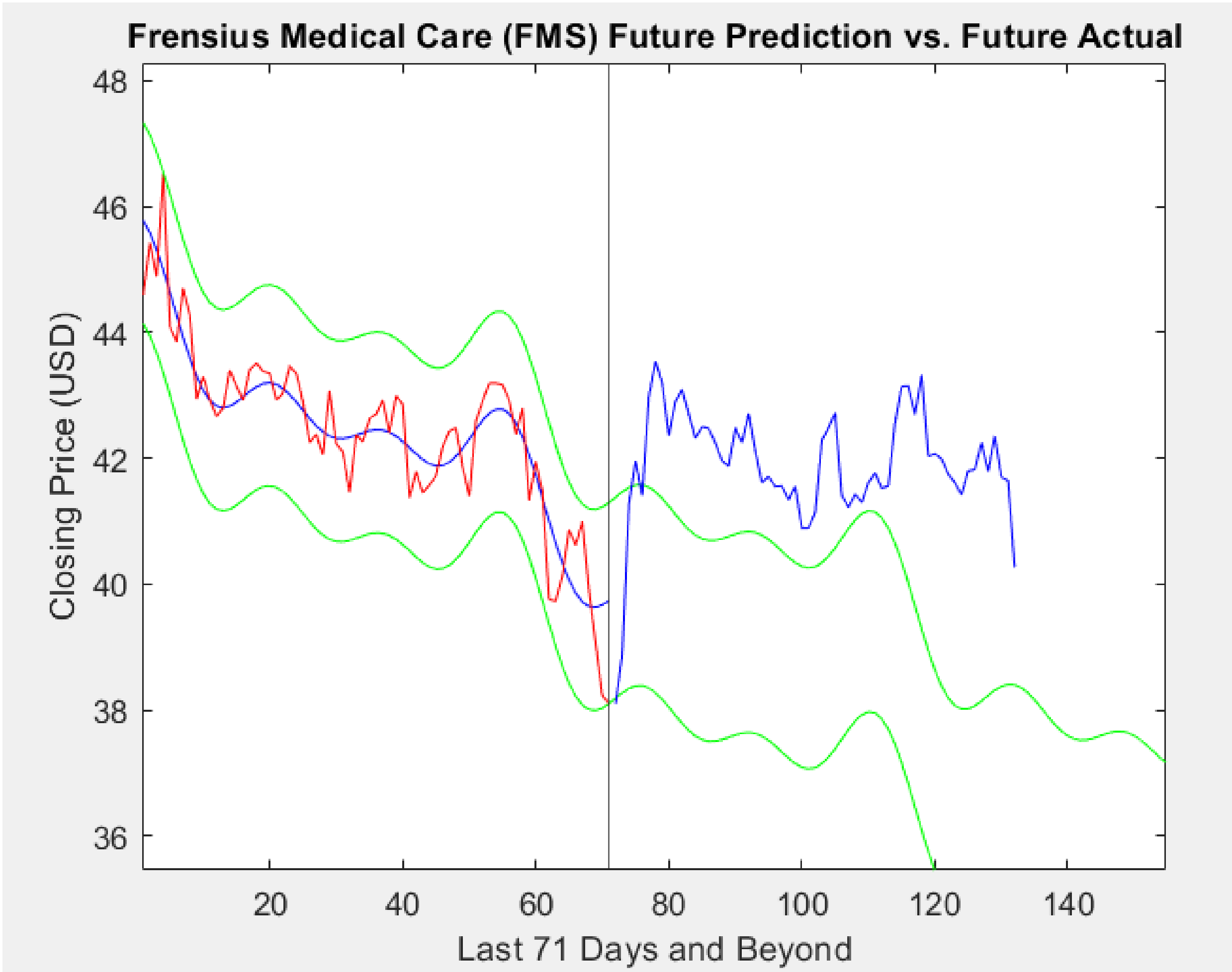

Frensius Medical Care (FMS) Autocorrelation
Autocorrelation
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
100
200
300
400
500
600
Lag


Frensius Medical Care (FMS) Relevant Period
Closing Price (USD)
47
46
45
44
43
42
41
40
39
38
0
10
20
30
40
50
60
70
80
Last 71 Days

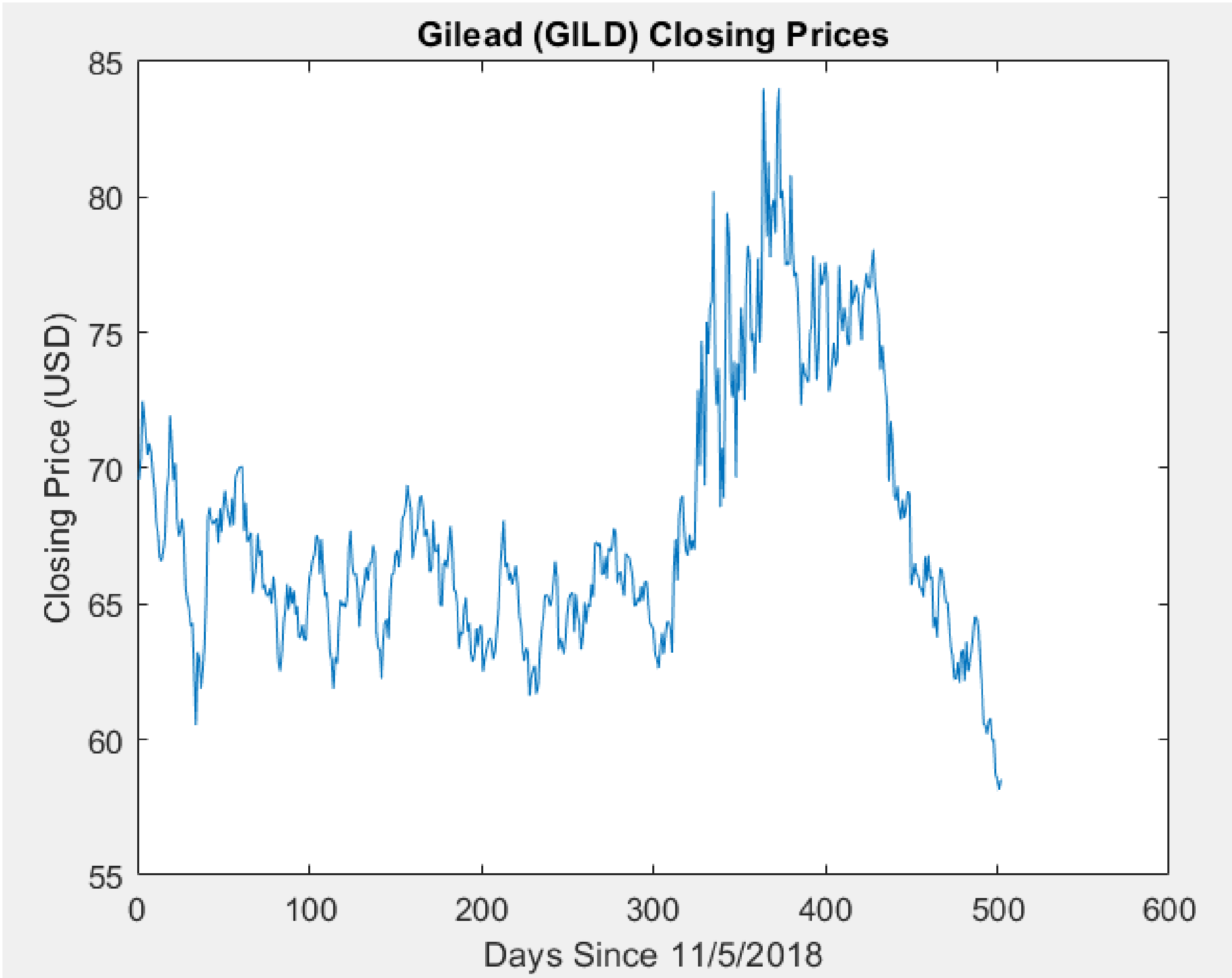

Frensius Medical Care (FMS) Closing Price /w Trendline
Closing Price (USD)
Last 71 Days
47
46
45
44
43
42
41
40
39
38
0
10
20
30
40
50
60
70
80

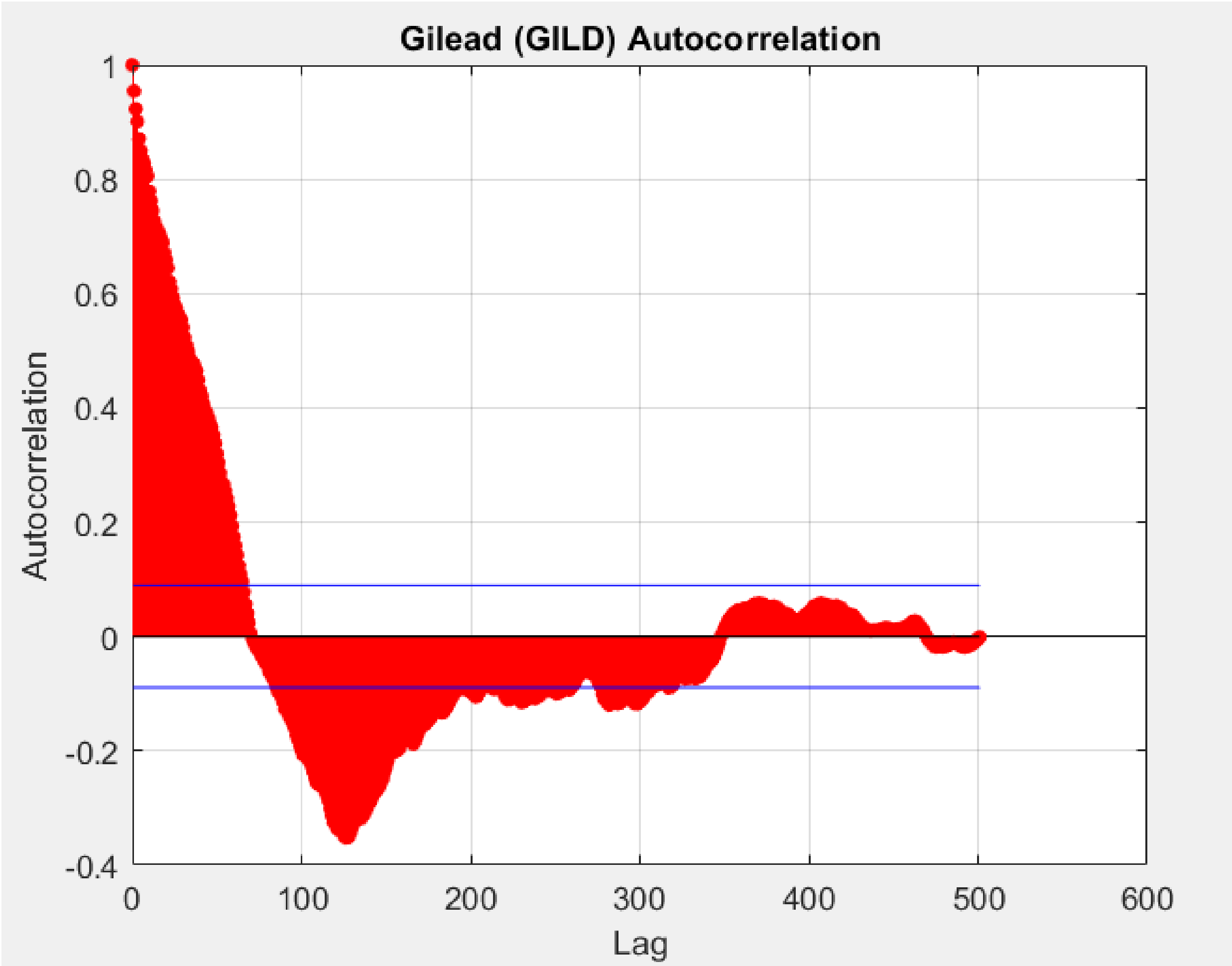

Frensius Medical Care (FMS) Trendline Residuals
Residual (USD)
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
0
10
20
30
40
50
60
70
80
Last 71 Days

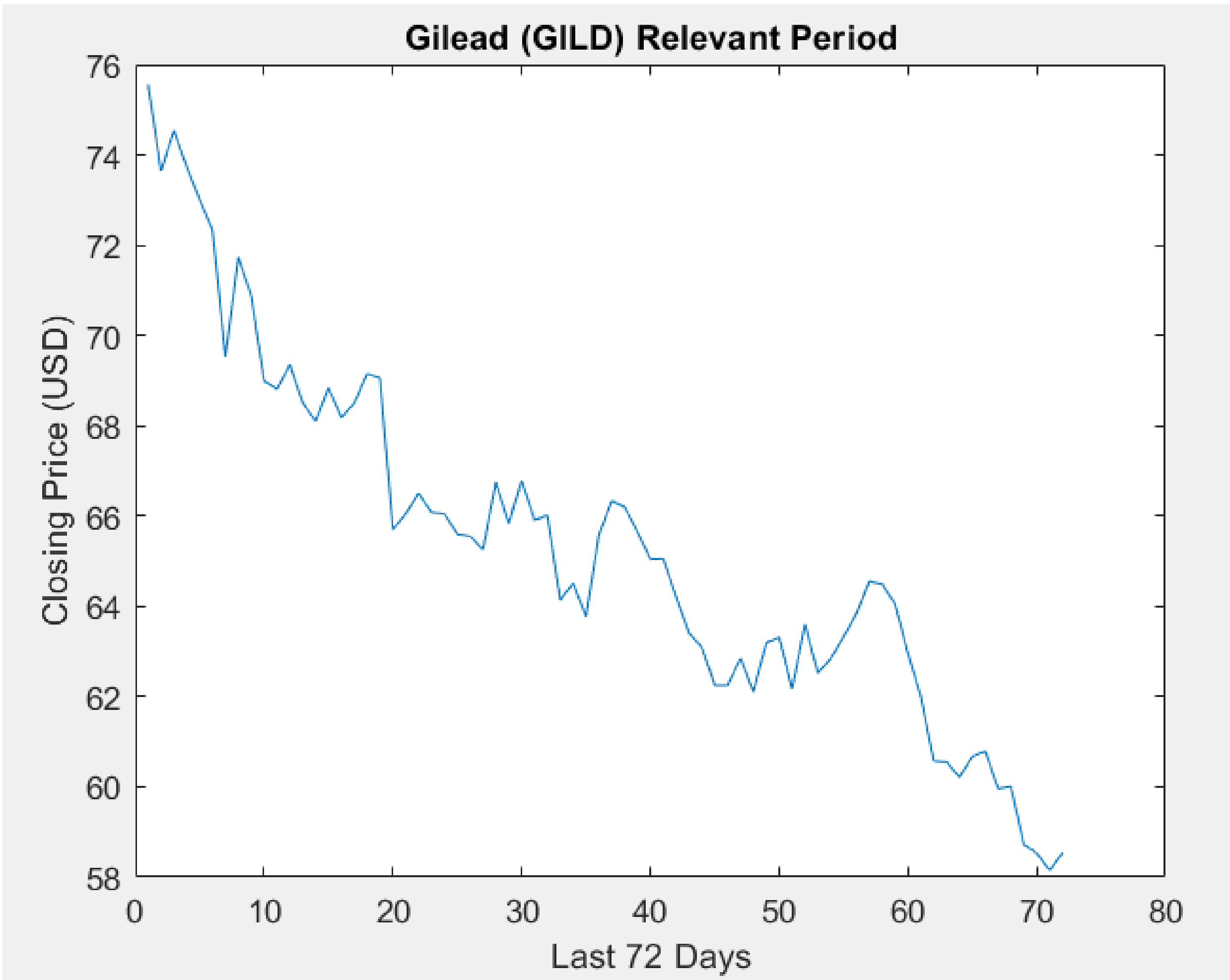

Frensius Medical Care (FMS) Base Model
Closing Price (USD)
47
46
45
44
43
42
41
40
39
38
0
10
20
30
40
50
60
70
80
Last 71 Days



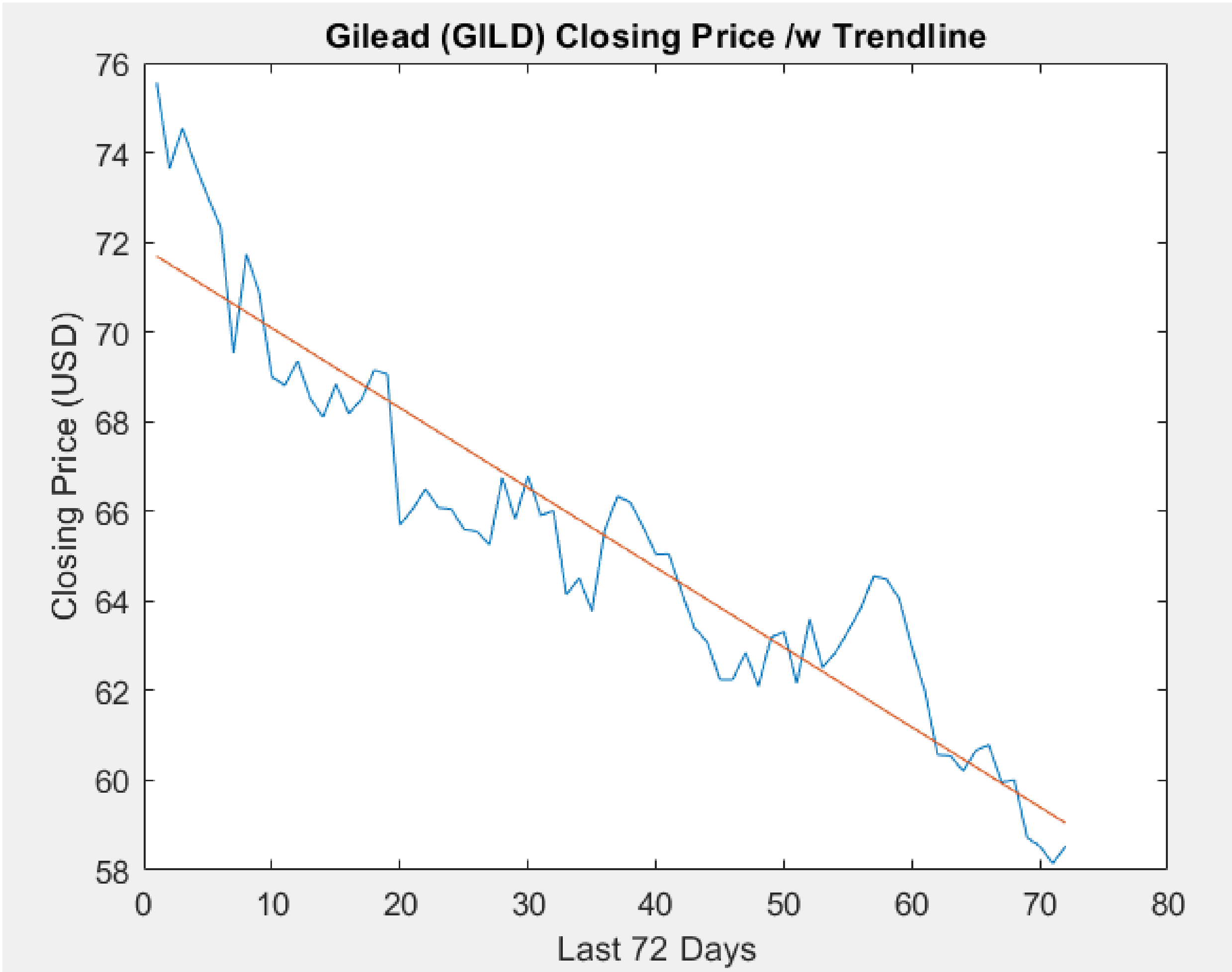
Frensius Medical Care (FMS) Future Prediction vs. Future Actual
48
46
44
42
40
38
36
Closing Price (USD)
20
40
60
80
100
120
140
Last 71 Days and Beyond


Gilead (GILD) Closing Prices
Closing Price (USD)
85
80
75
70
65
60
55
0
100
200
300
400
500
600
Days Since 11/5/2018

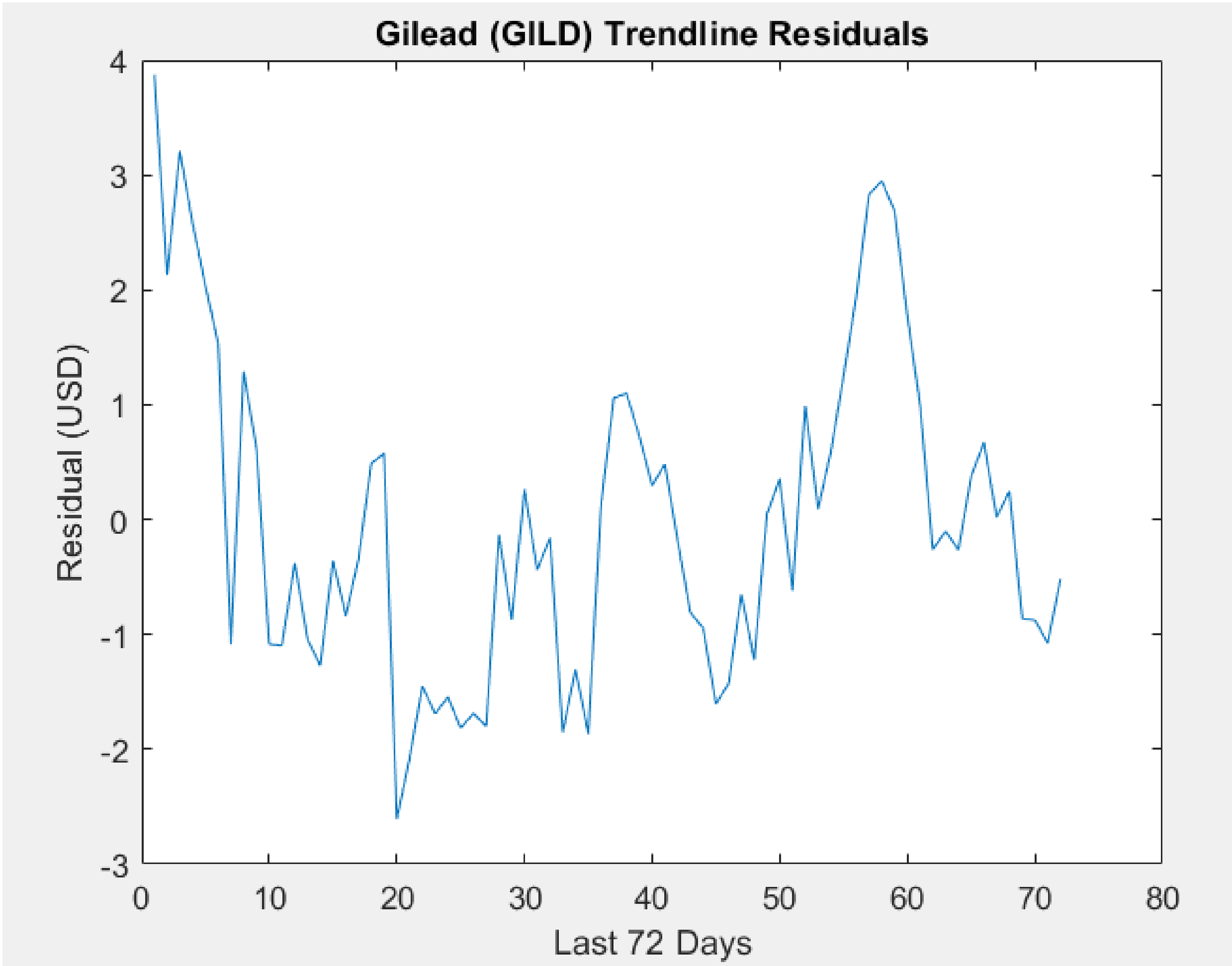

Gilead (GILD) Autocorrelation
Autocorrelation
Lag
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
100
200
300
400
500
600



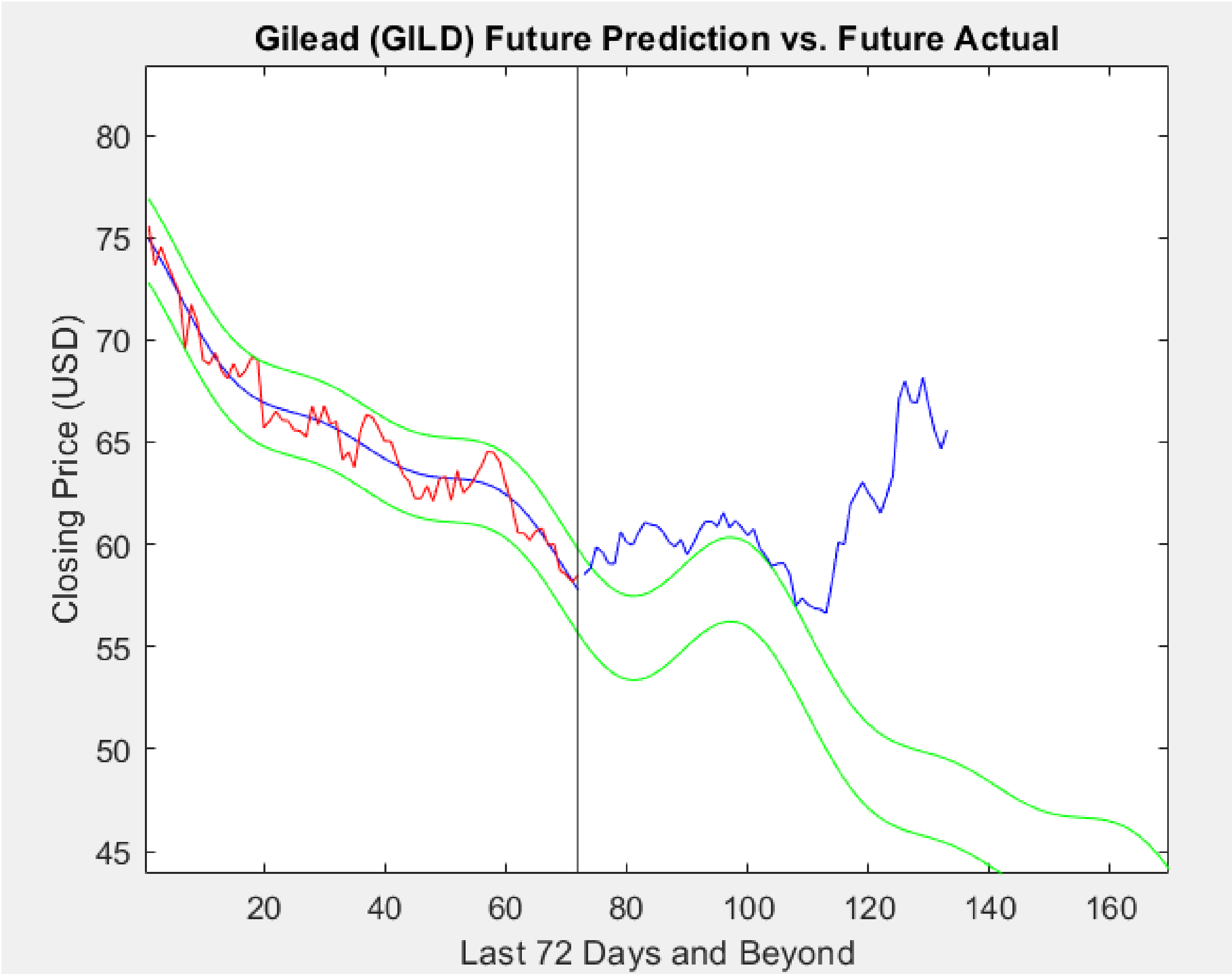
Gilead (GILD) Relevant Period
Closing Price (USD)
Last 72 Days
76
74
72
70
68
66
64
62
60
58
0
10
20
30
40
50
60
70
80



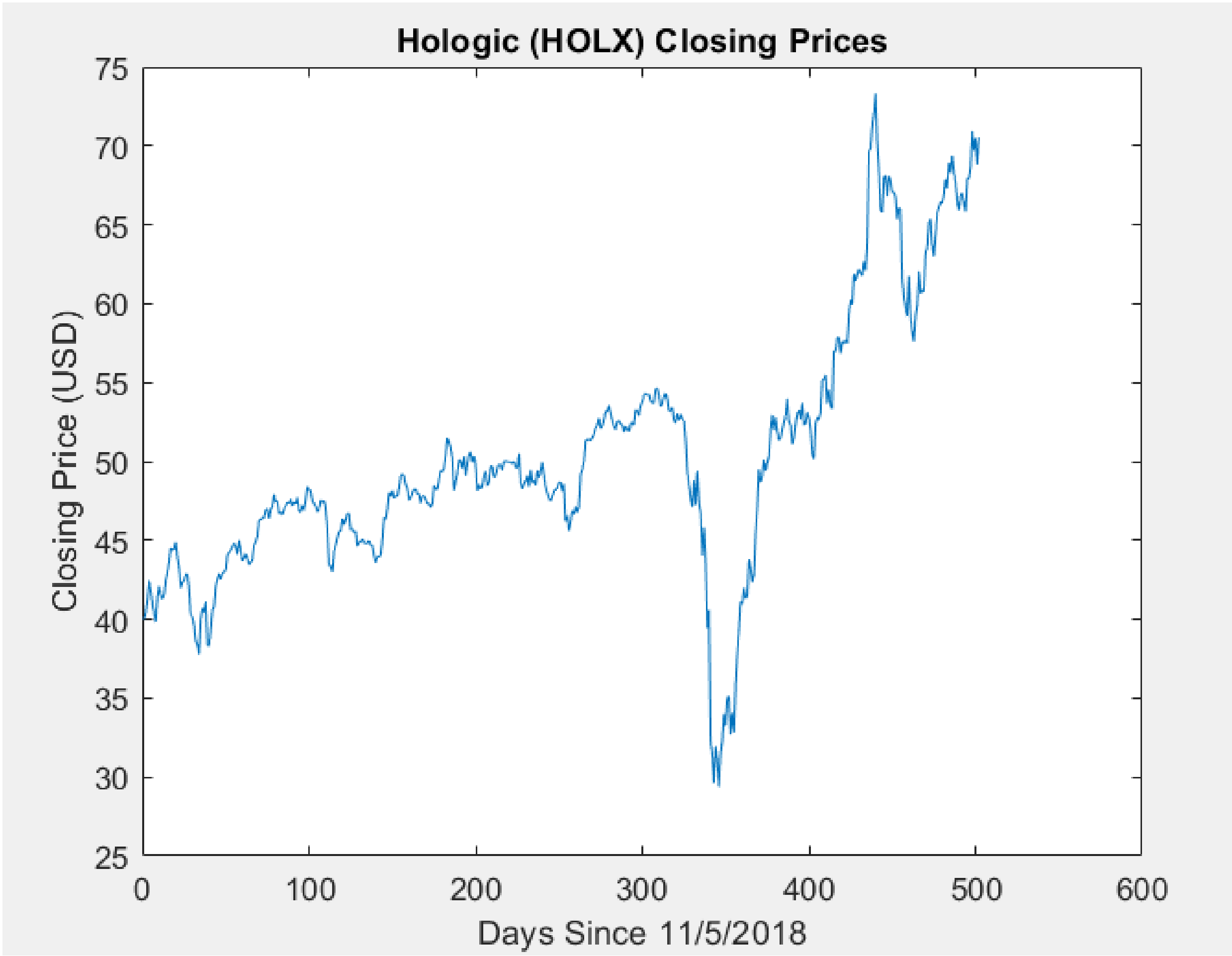
Gilead (GILD) Closing Price /w Trendline
Closing Price (USD)
76
74
72
70
68
66
64
62
60
58
0
10
20
30
40
50
60
70
80
Last 72 Days

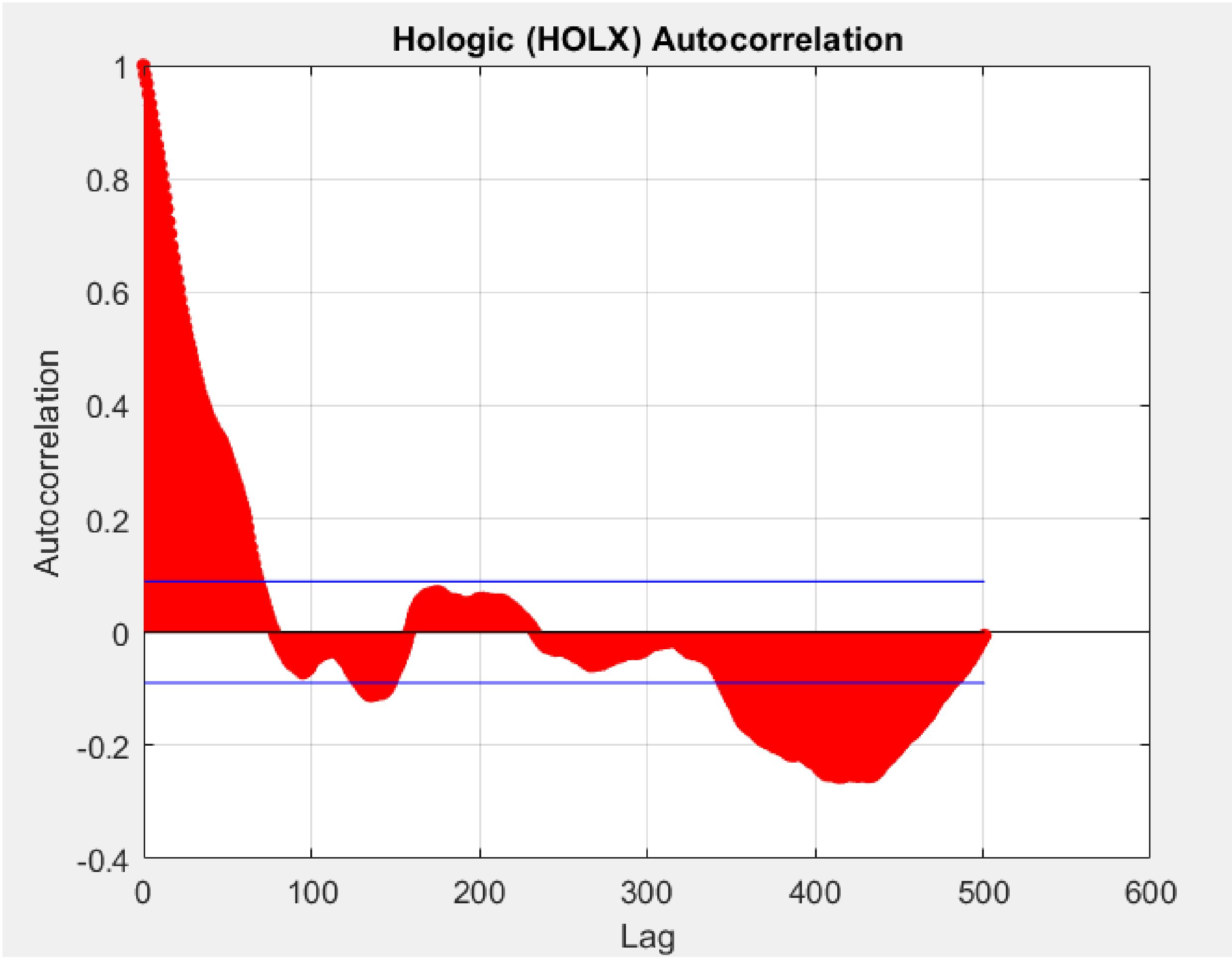

Gilead (GILD) Trendline Residuals
Residual (USD)
4
3
2
1
0
-1
-2
-3
0
10
20
30
40
50
60
70
80
Last 72 Days

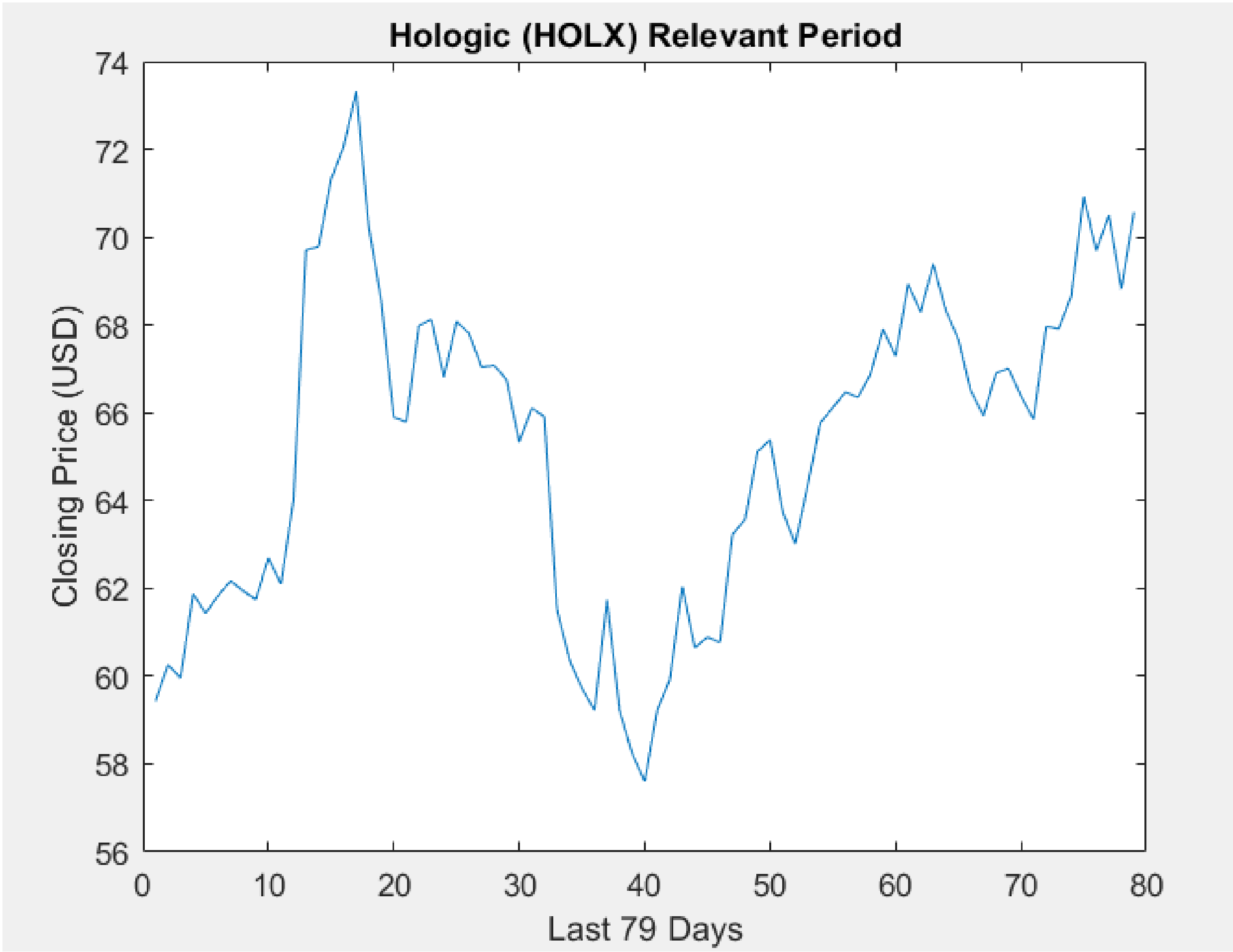
Gilead (GILD) Base Model
Closing Price (USD)
76
74
72
70
68
66
64
62
60
58
56
0
10
20
30
40
50
60
70
80
Last 72 Days

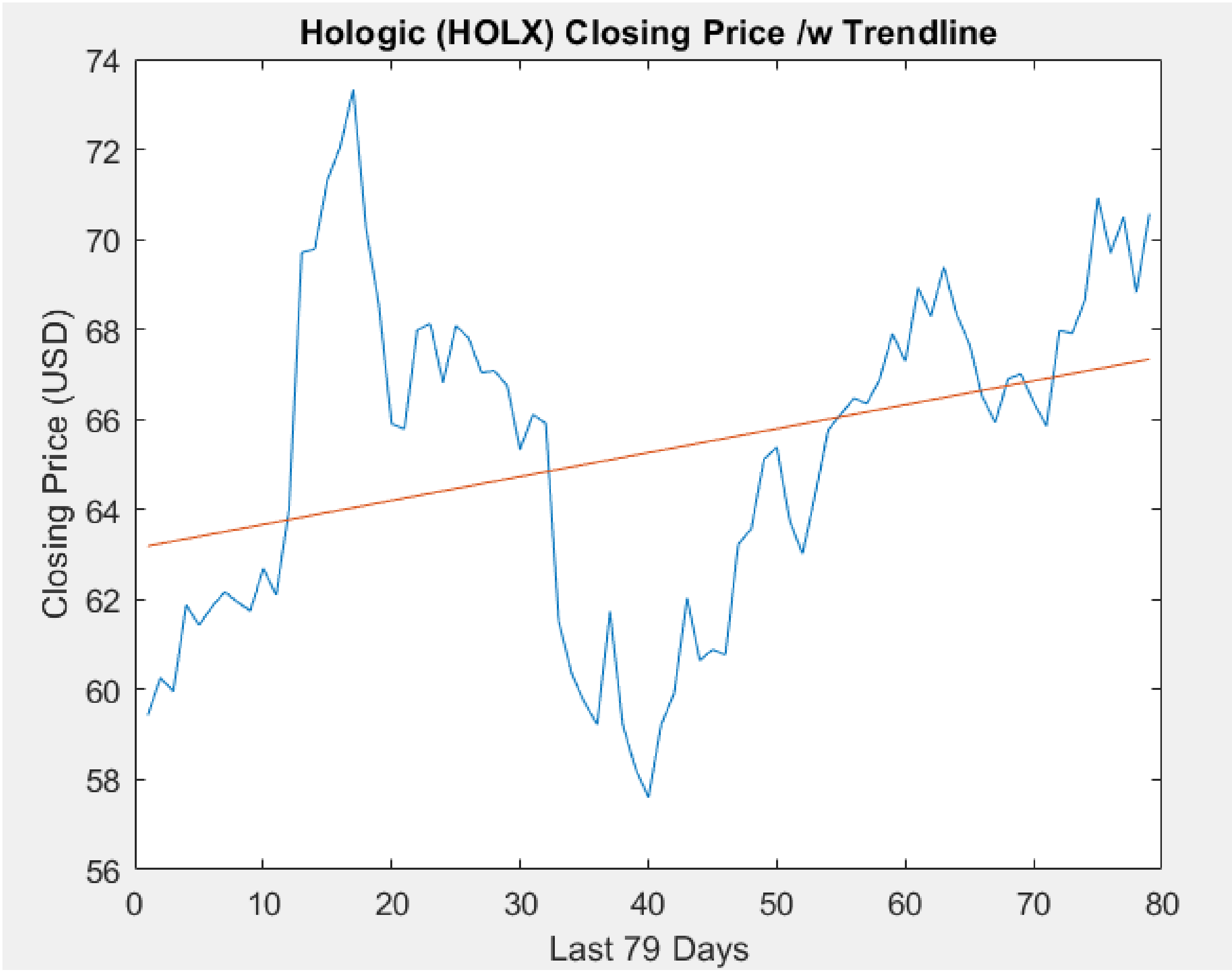


Gilead (GILD) Future Prediction vs. Future Actual
Closing Price (USD)
80
75
70
65
60
55
50
45
20
40
60
80
100
120
140
160
Last 72 Days and Beyond

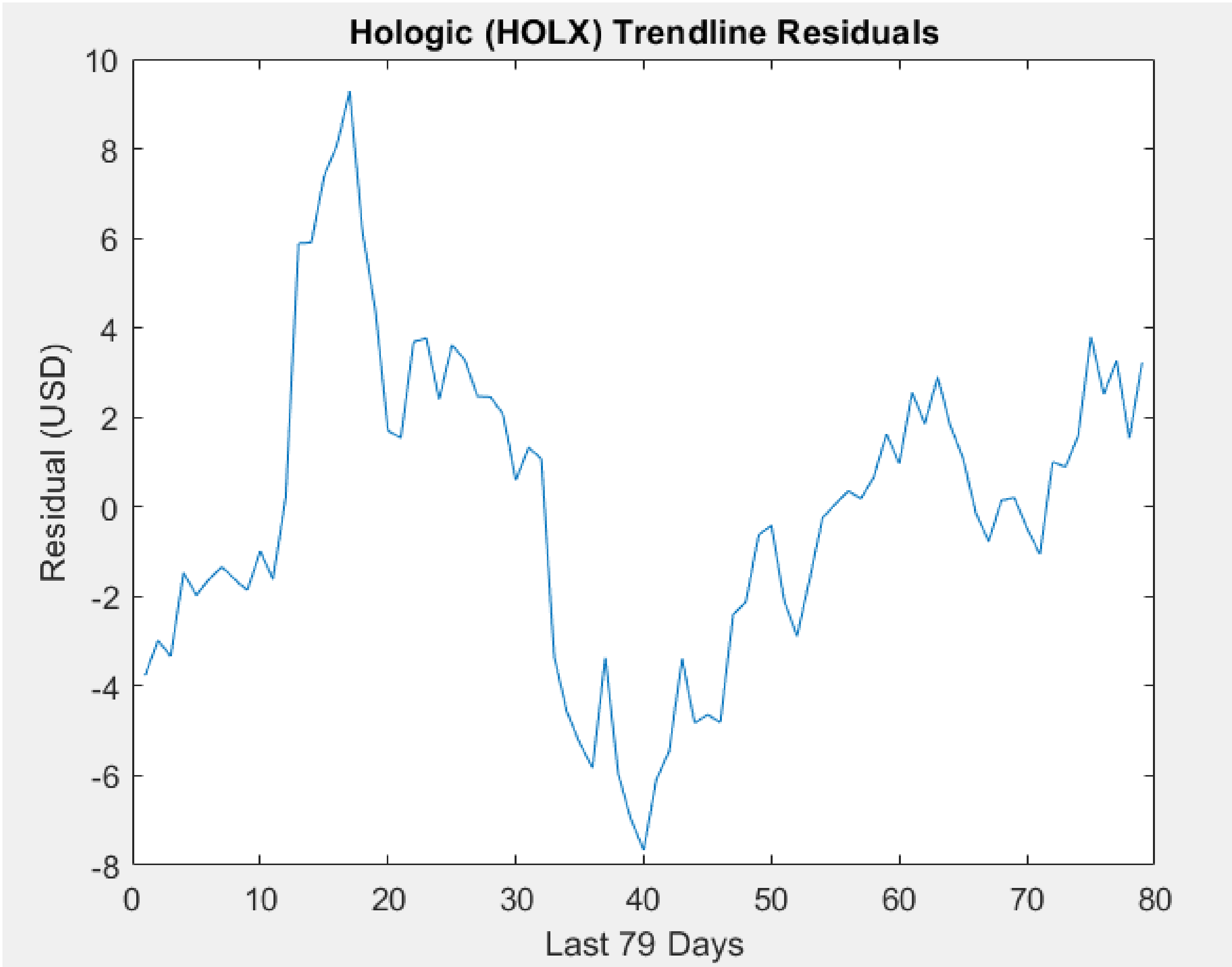

Hologic (HOLX) Closing Prices
Closing Price (USD)
75
70
65
60
55
50
45
40
35
30
25
0
100
200
300
400
500
600
Days Since 11/5/2018


Hologic (HOLX) Autocorrelation
Autocorrelation
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
100
200
300
400
500
600
Lag

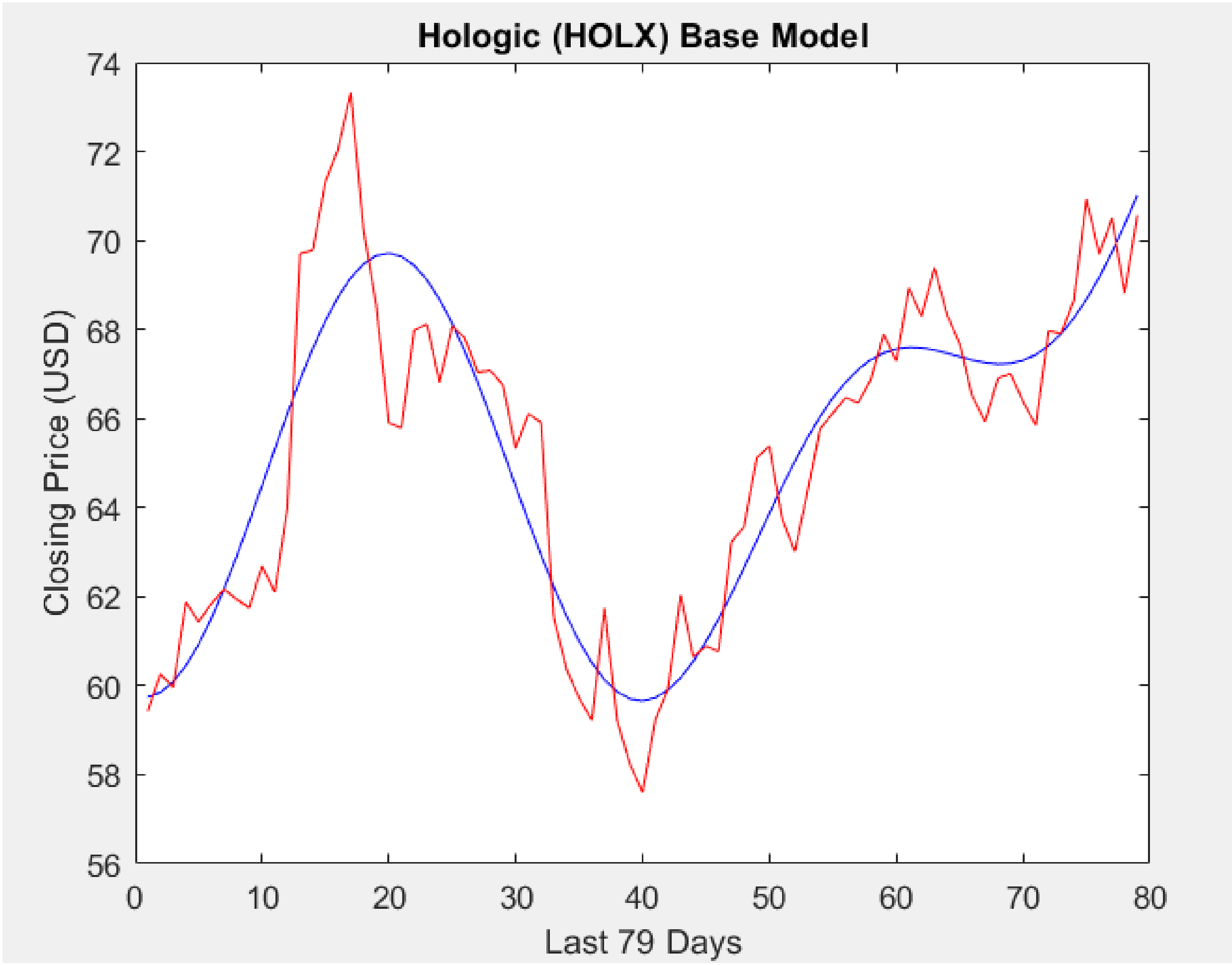

Hologic (HOLX) Relevant Period
Closing Price (USD)
74
72
70
68
66
64
62
60
58
56
0
10
20
30
40
50
60
70
80
Last 79 Days

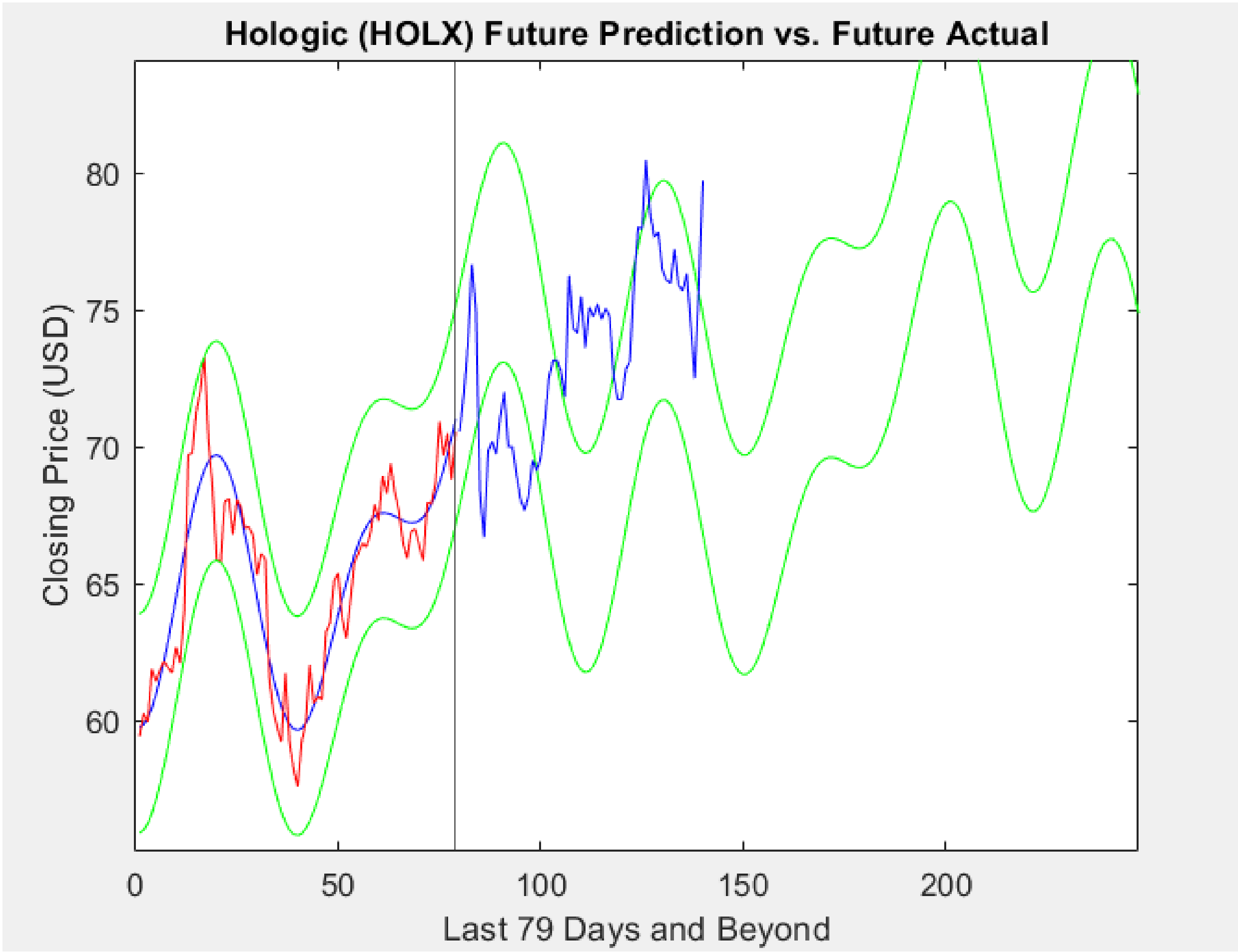


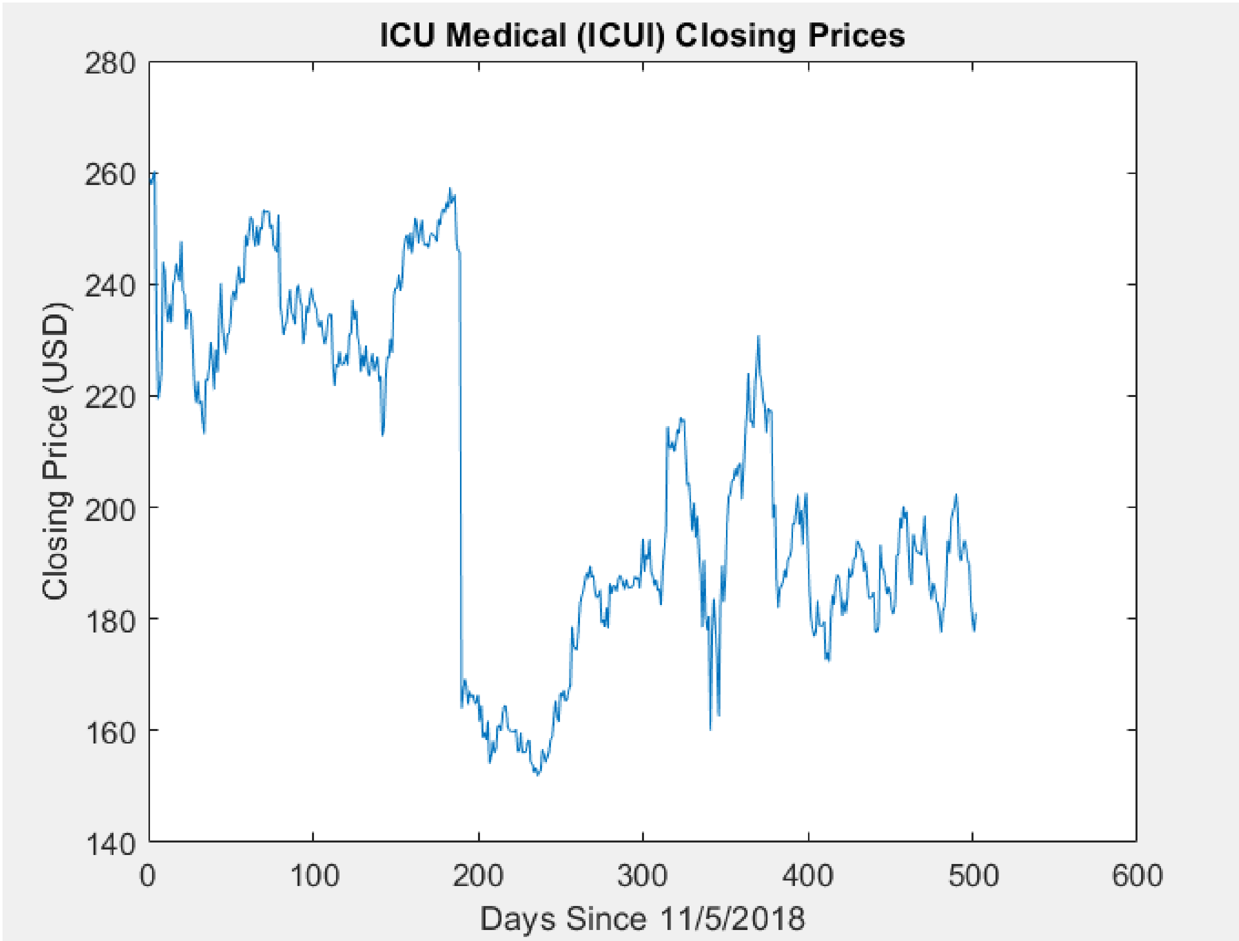
Hologic (HOLX) Closing Price /w Trendline
Closing Price (USD)
Last 79 Days
74
72
70
68
66
64
62
60
58
56
0
10
20
30
40
50
60
70
80

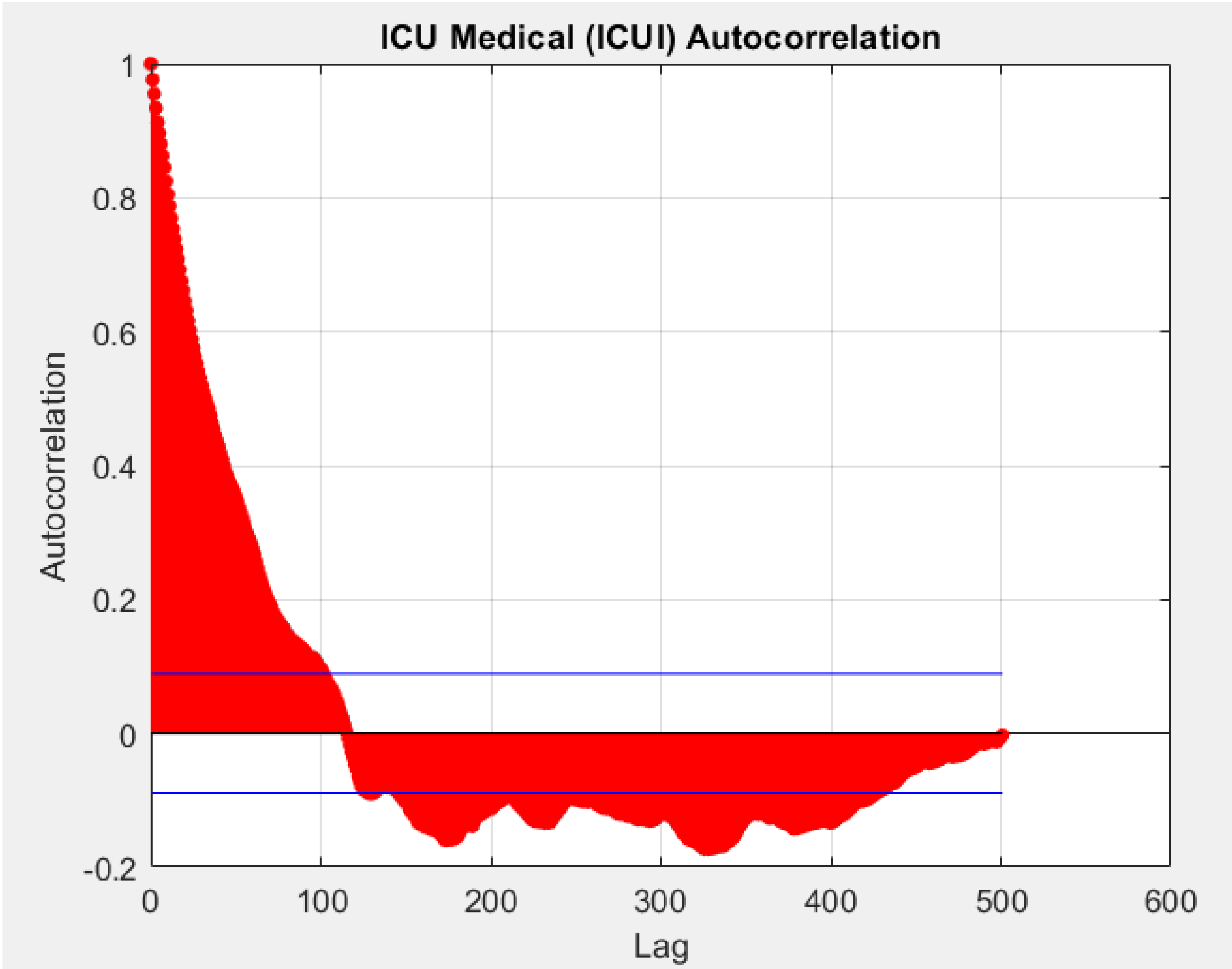


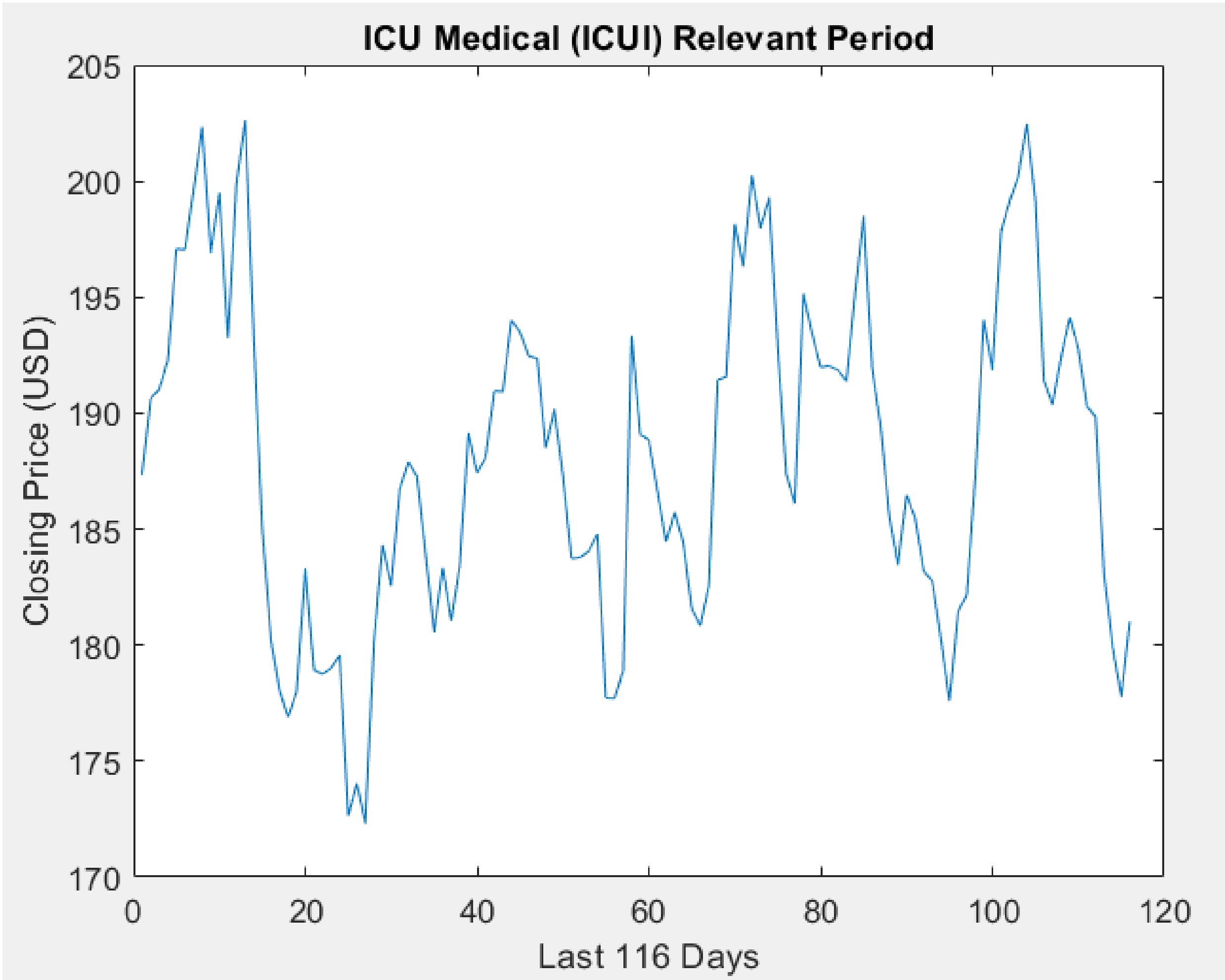
Hologic (HOLX) Trendline Residuals
Residual (USD)
10
8
6
4
2
0
-2
-4
-6
-8
0
10
20
30
40
50
60
70
80
Last 79 Days

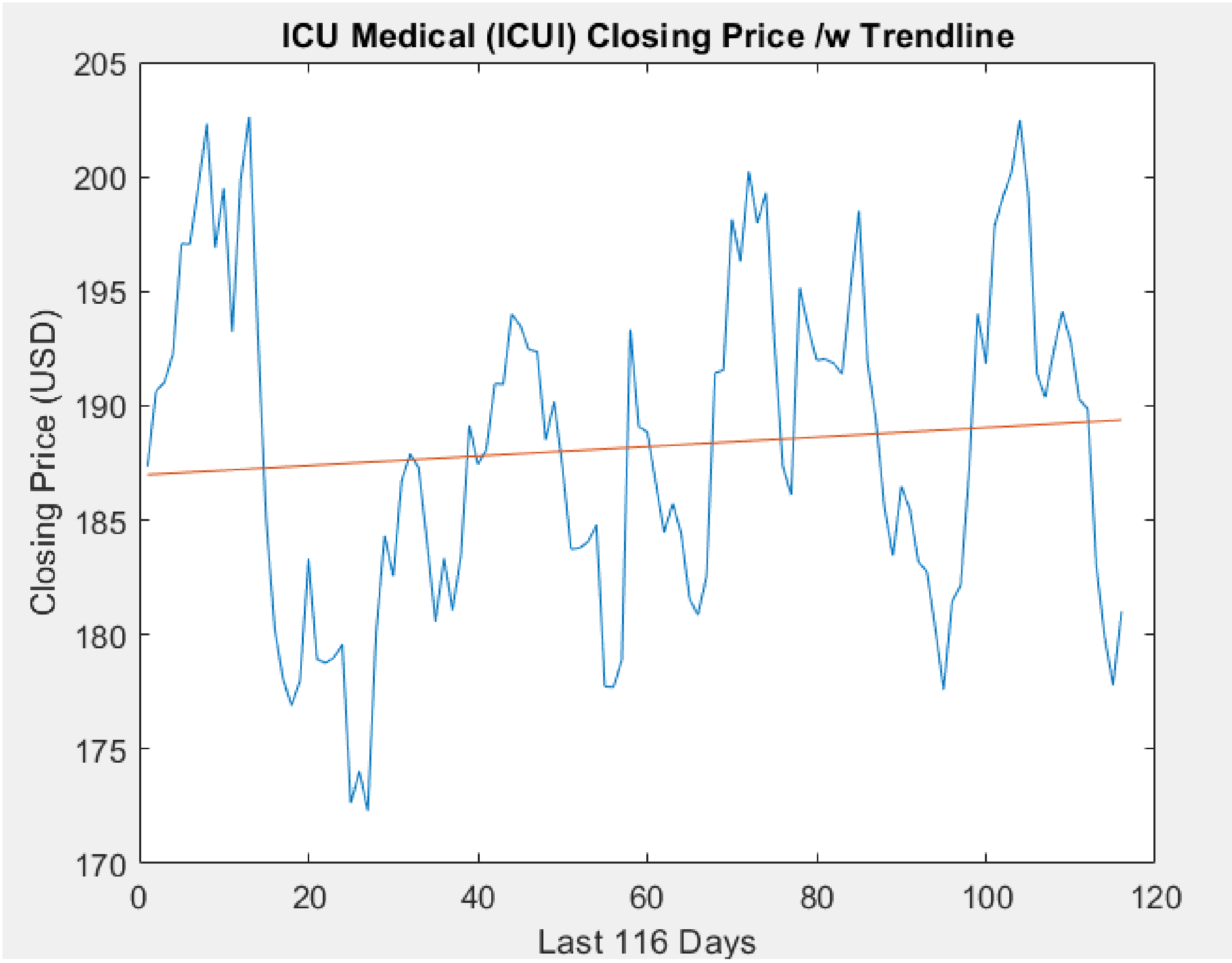

Hologic (HOLX) Base Model
Closing Price (USD)
Last 79 Days
74
72
70
68
66
64
62
60
58
56
0
10
20
30
40
50
60
70
80


Hologic (HOLX) Future Prediction vs. Future Actual
Closing Price (USD)
80
75
70
65
60
0
50
100
150
200
Last 79 Days and Beyond

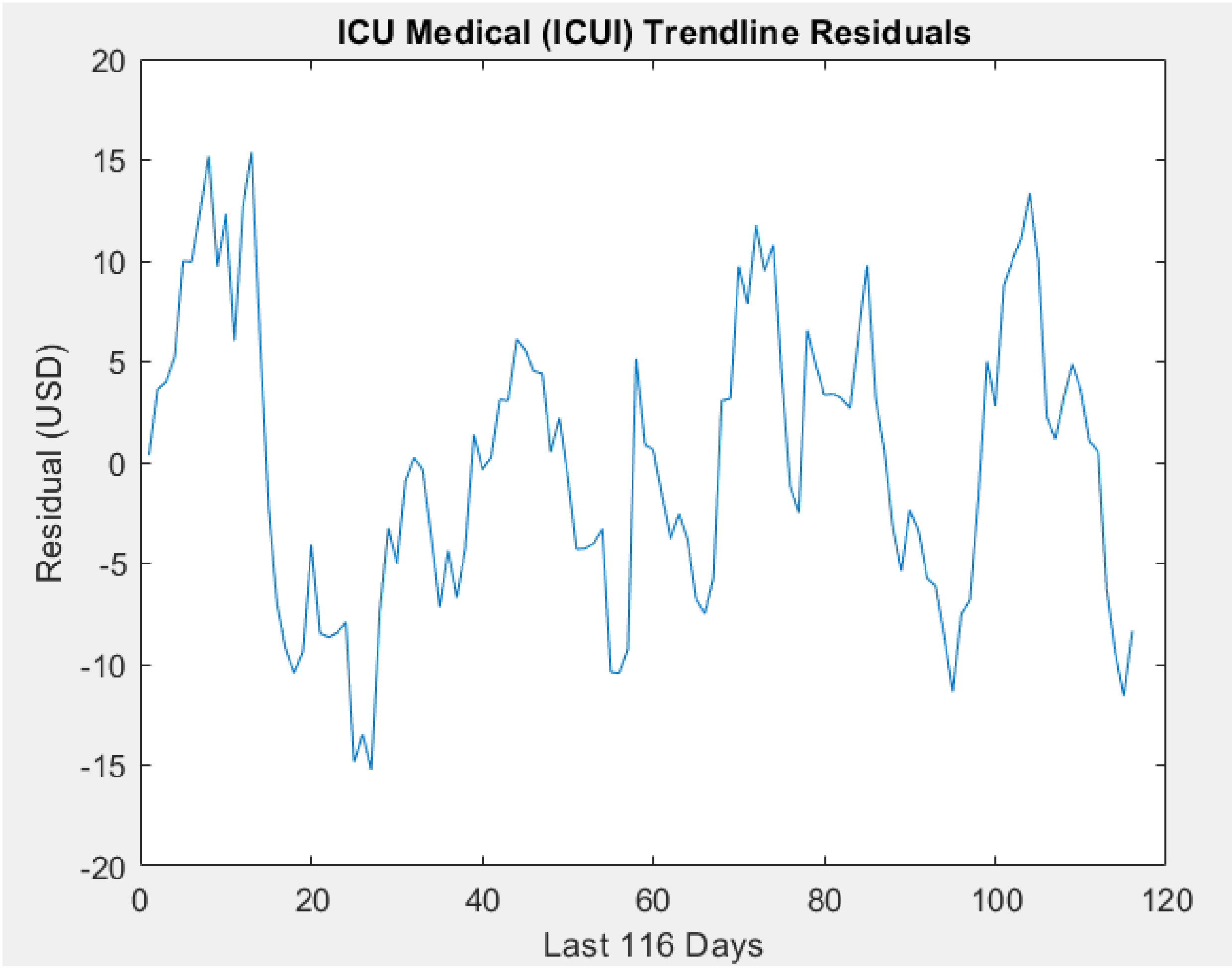

ICU Medical (ICUI) Closing Prices
Closing Price (USD)
280
260
240
220
200
180
160
140
0
100
200
300
400
500
600
Days Since 11/5/2018

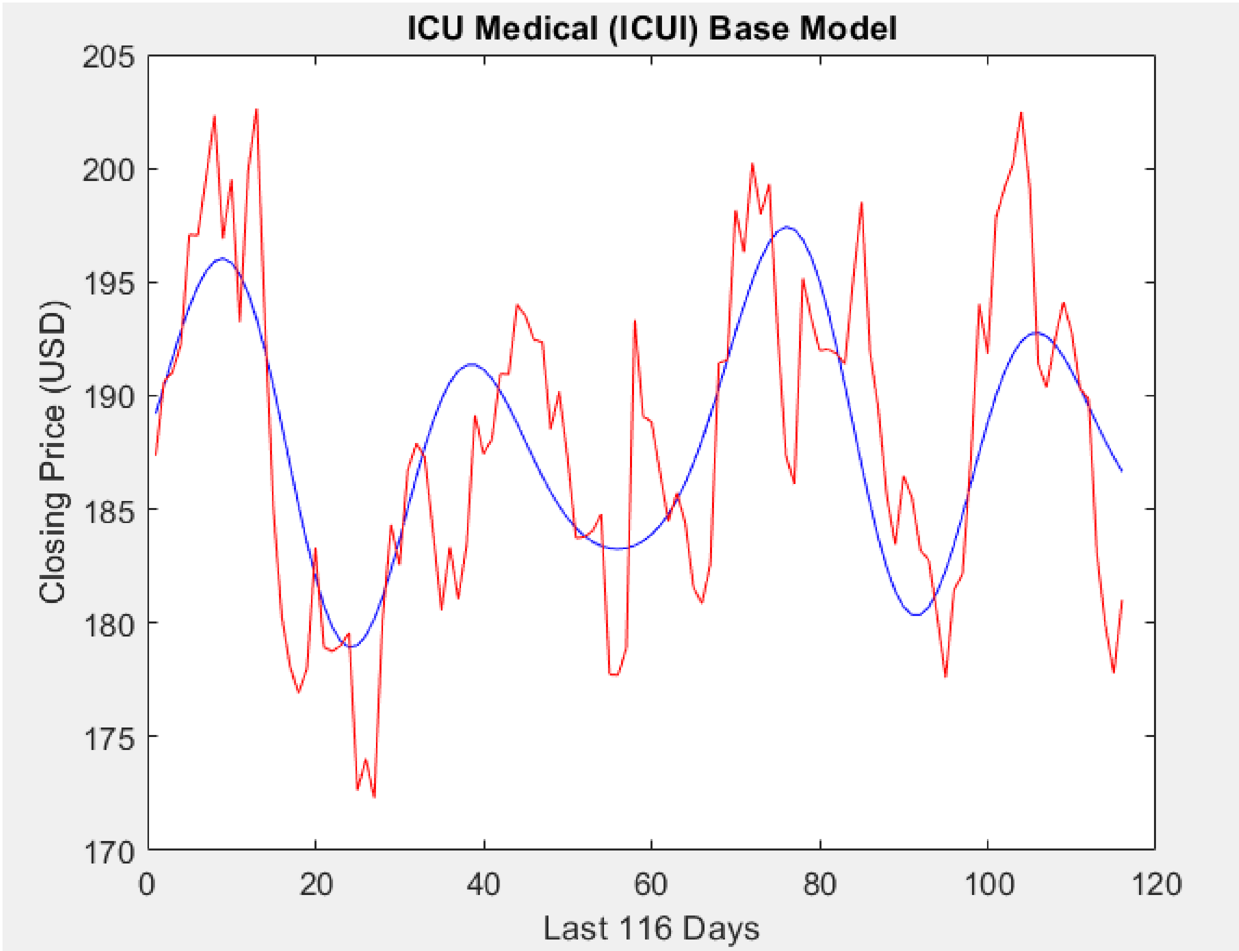

ICU Medical (ICUI) Autocorrelation
Autocorrelation
Lag
1
0.8
0.6
0.4
0.2
0
-0.2
0
100
200
300
400
500
600

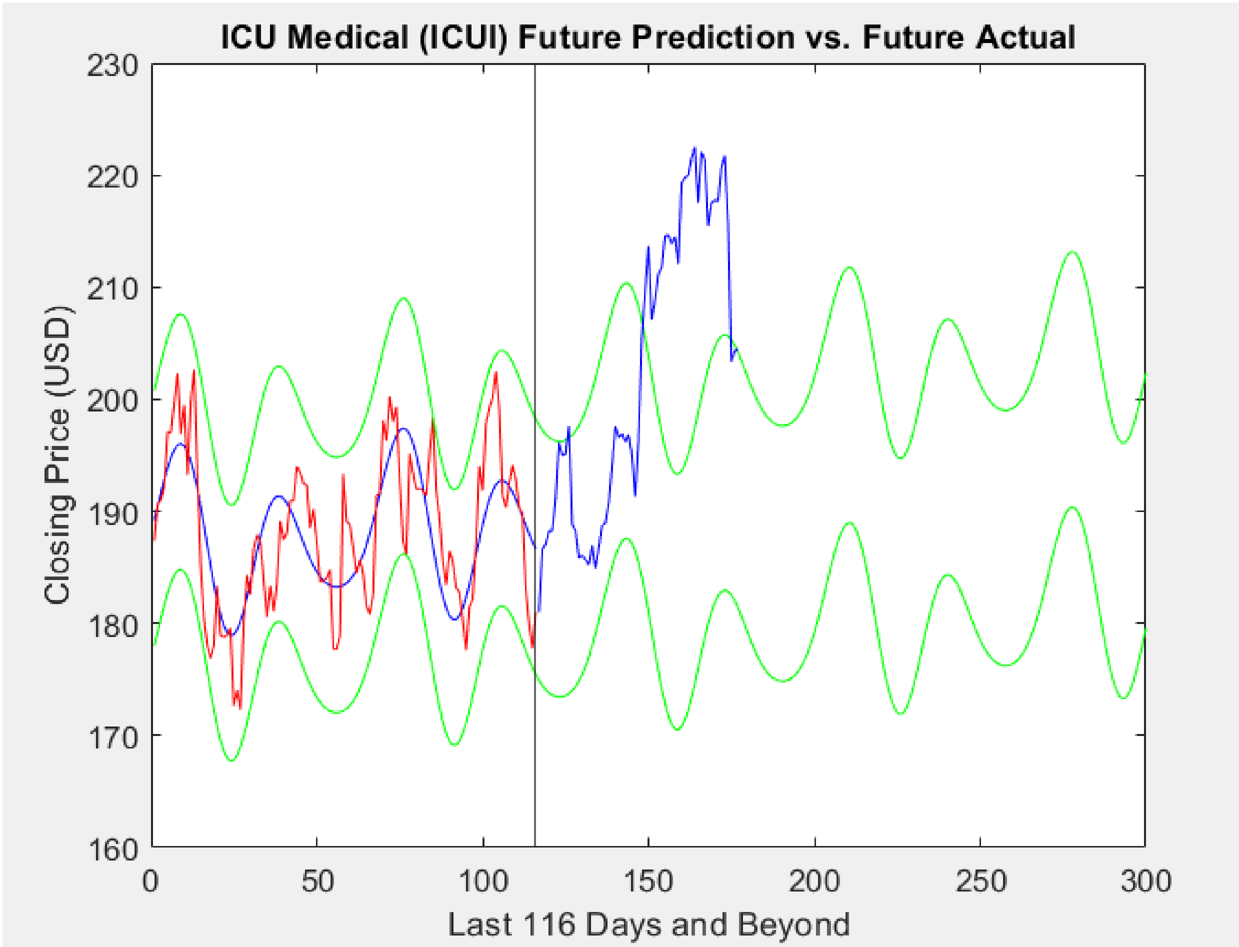

ICU Medical (ICUI) Relevant Period
Closing Price (USD)
205
200
195
190
185
180
175
170
0
20
40
60
80
100
120
Last 116 Days



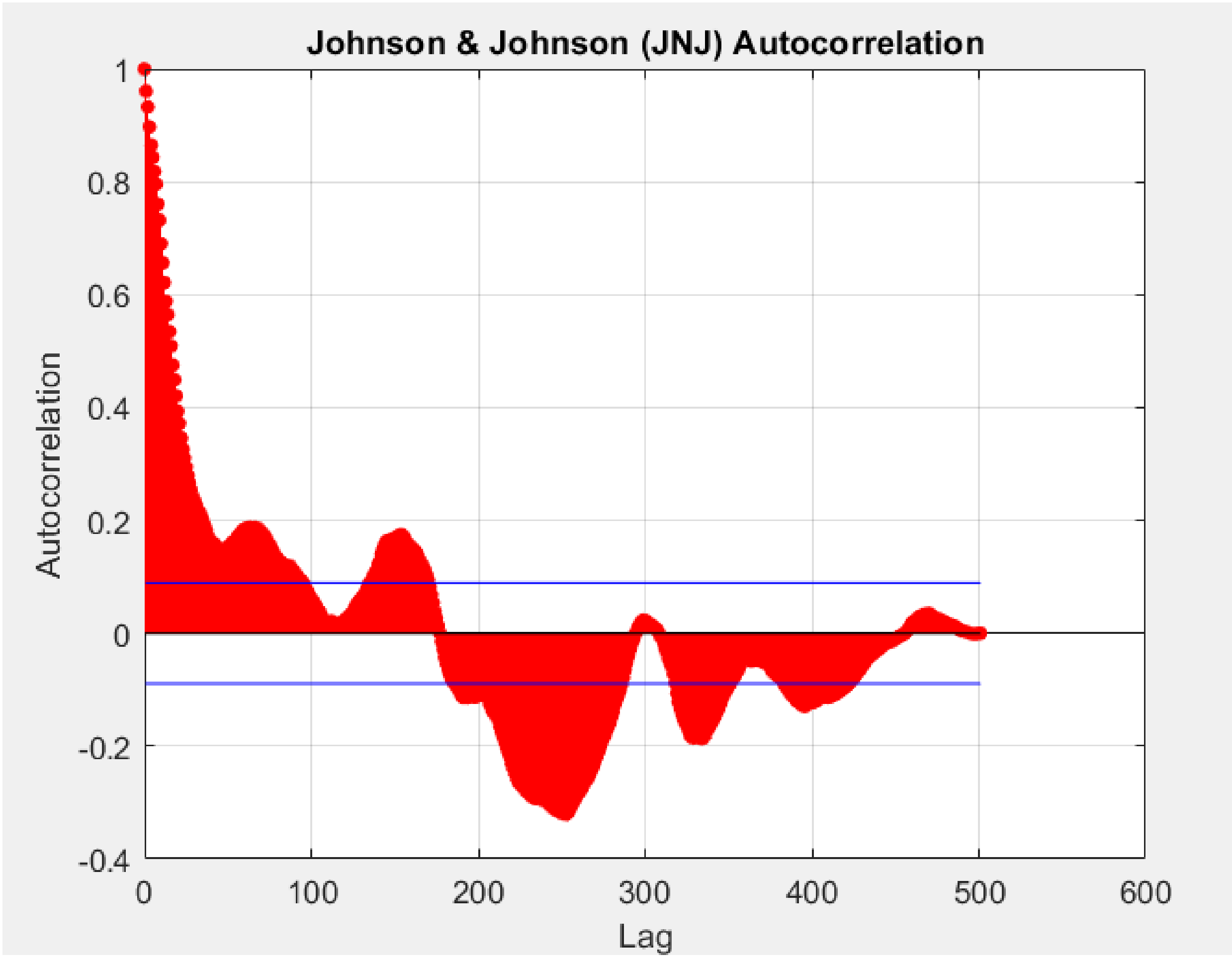
ICU Medical (ICUI) Closing Price /w Trendline
205
200
195
190
185
180
175
170
Closing Price (USD)
0
20
40
60
80
100
120
Last 116 Days

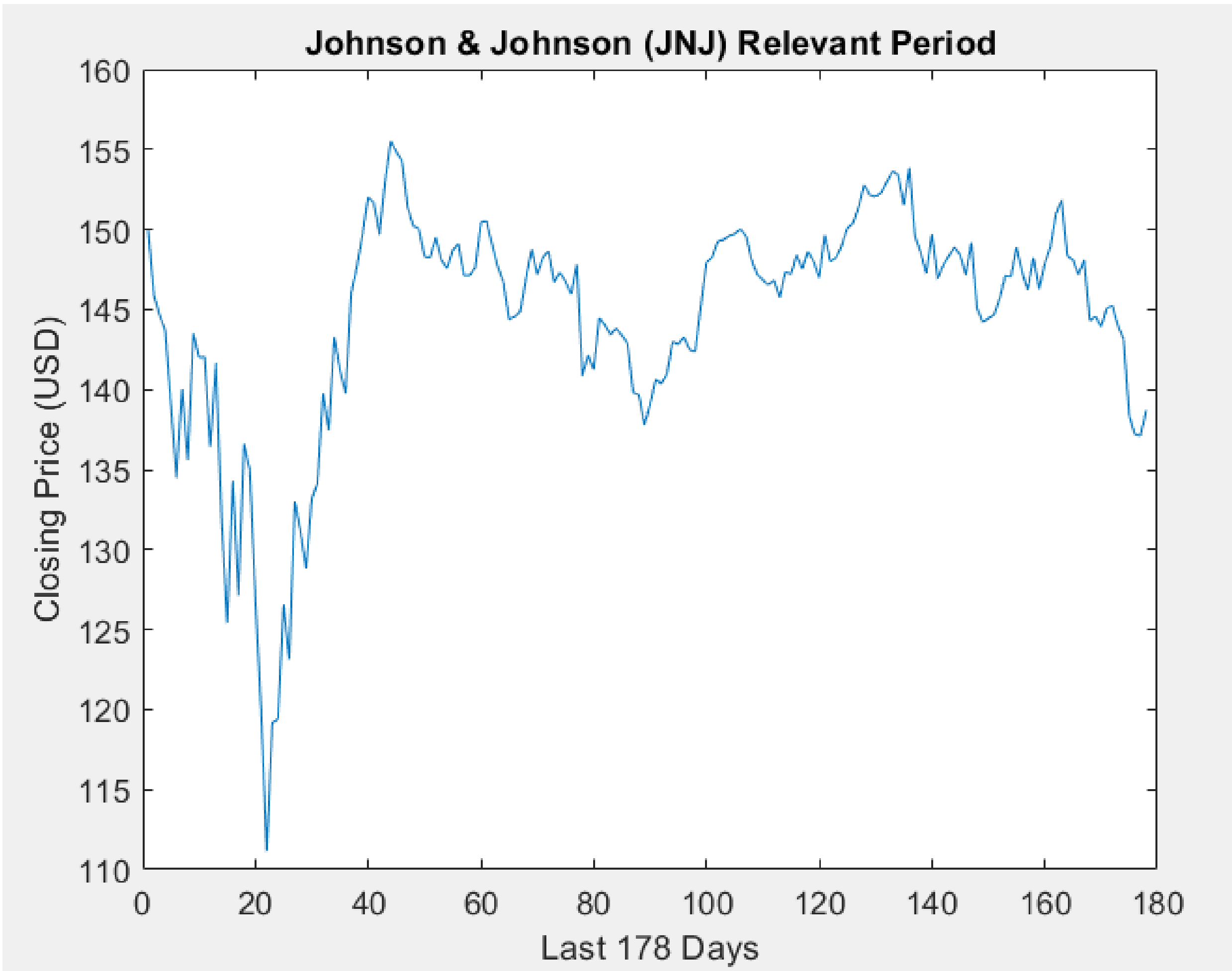

ICU Medical (ICUI) Trendline Residuals
Residual (USD)
Last 116 Days
20
15
10
5
0
-5
-10
-15
-20
0
20
40
60
80
100
120

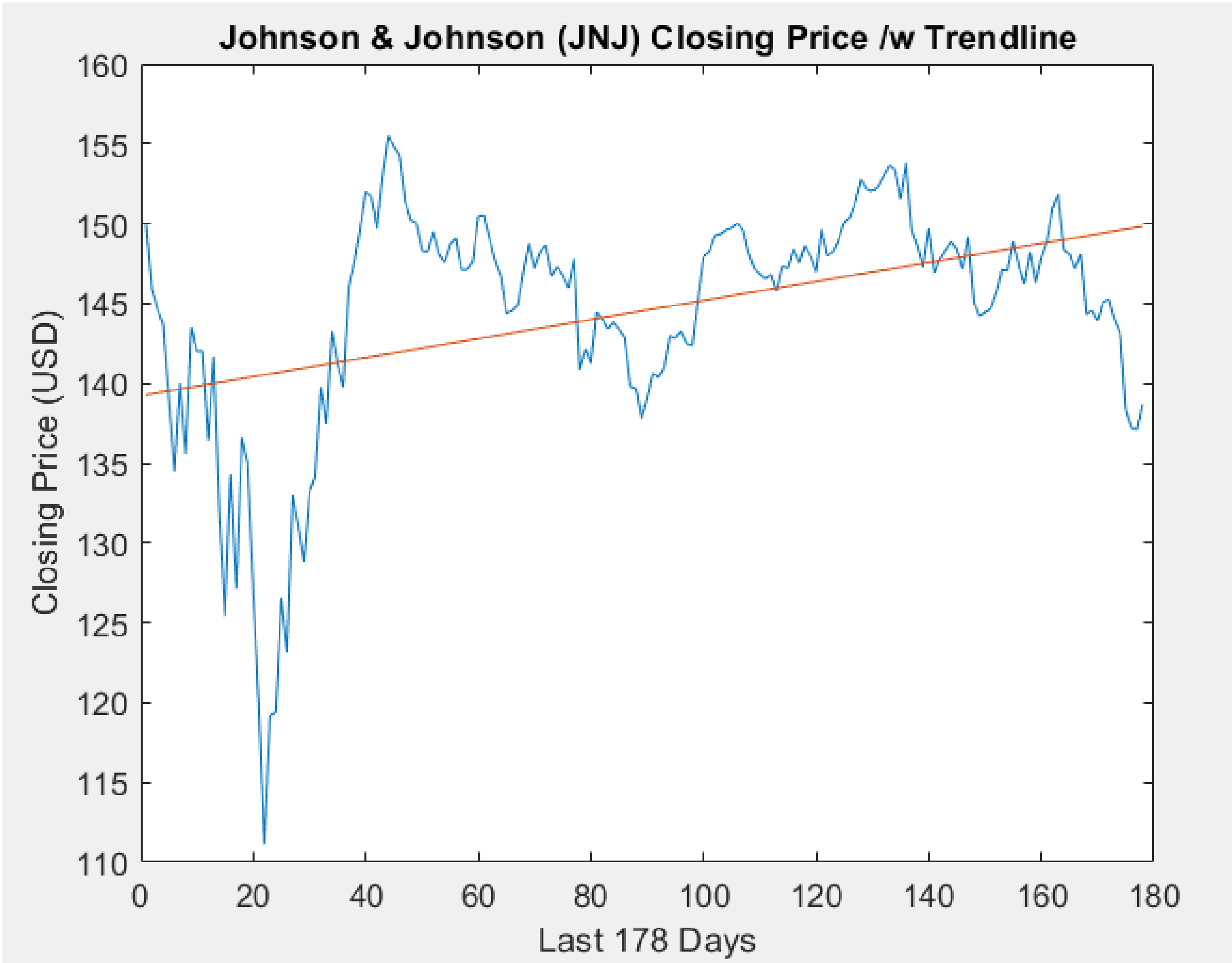

ICU Medical (ICUI) Base Model
Closing Price (USD)
Last 116 Days
205
200
195
190
185
180
175
170
0
20
40
60
80
100
120

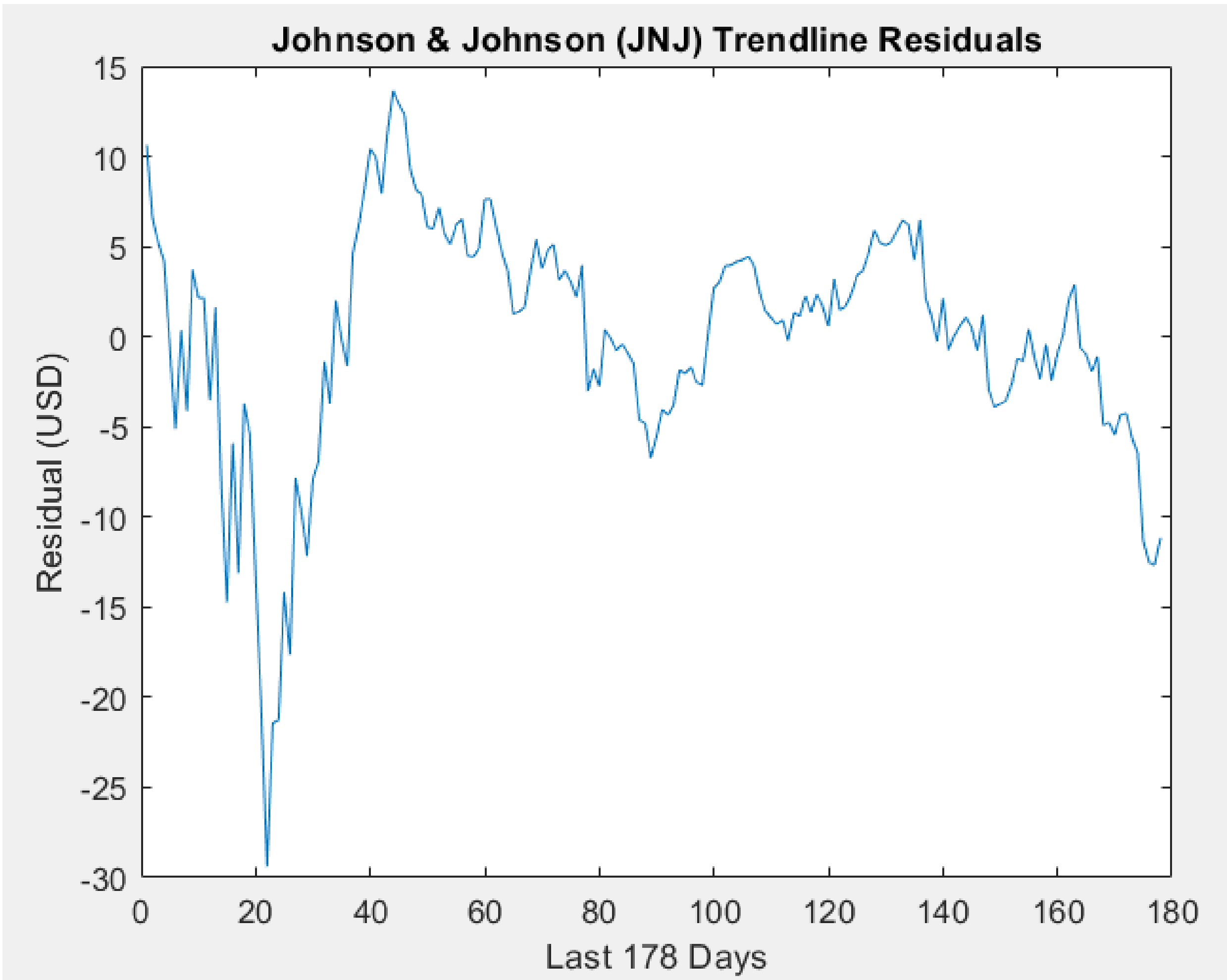

ICU Medical (ICUI) Future Prediction vs. Future Actual
Closing Price (USD)
230
220
210
200
190
180
170
160
0
50
100
150
200
250
300
Last 116 Days and Beyond

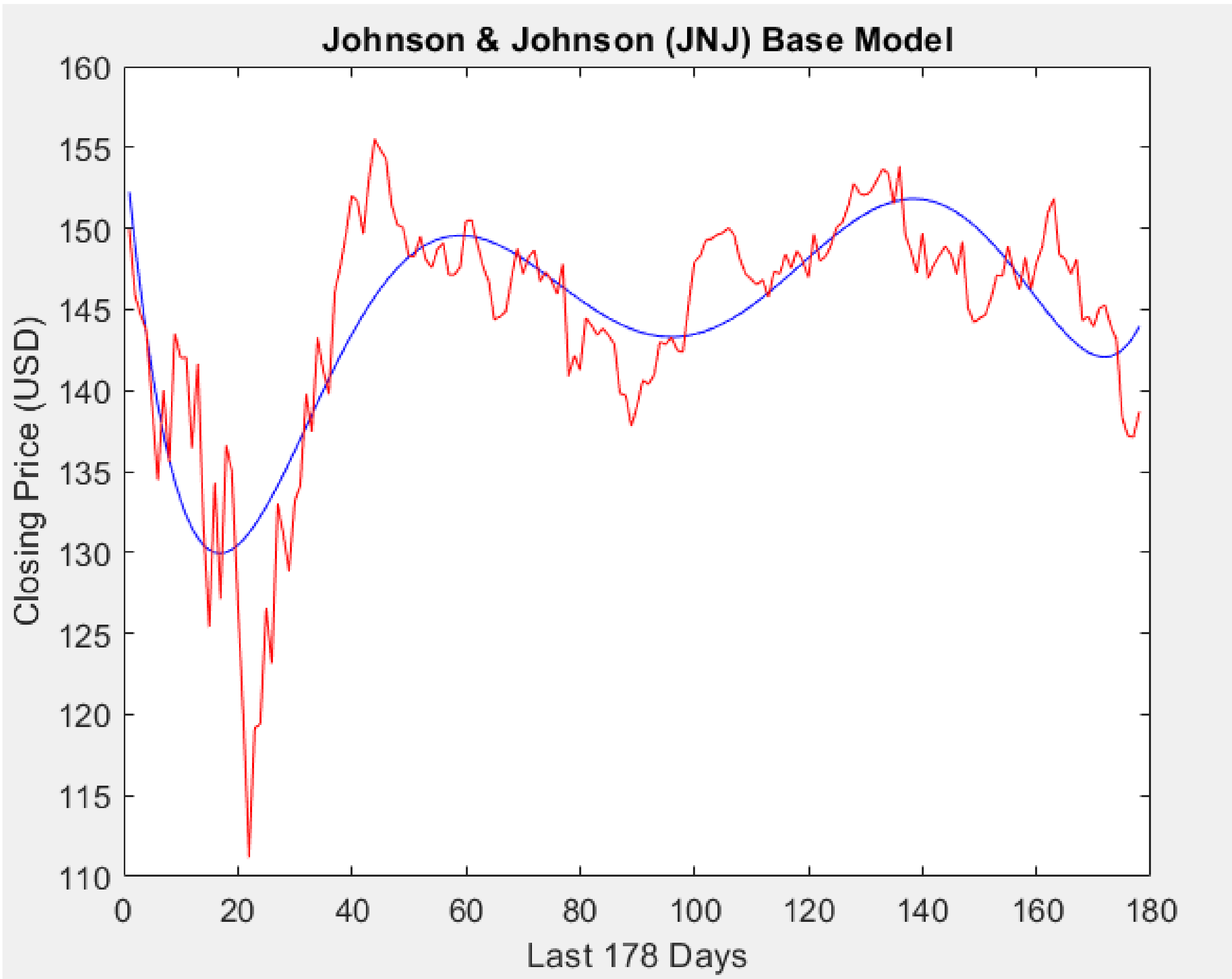

Johnson & Johnson (JNJ) Closing Prices
Closing Price (USD)
Days Since 11/5/2018
160
155
150
145
140
135
130
125
120
115
110
0
100
200
300
400
500
600


Johnson & Johnson (JNJ) Autocorrelation
Autocorrelation
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
100
200
300
400
500
600
Lag

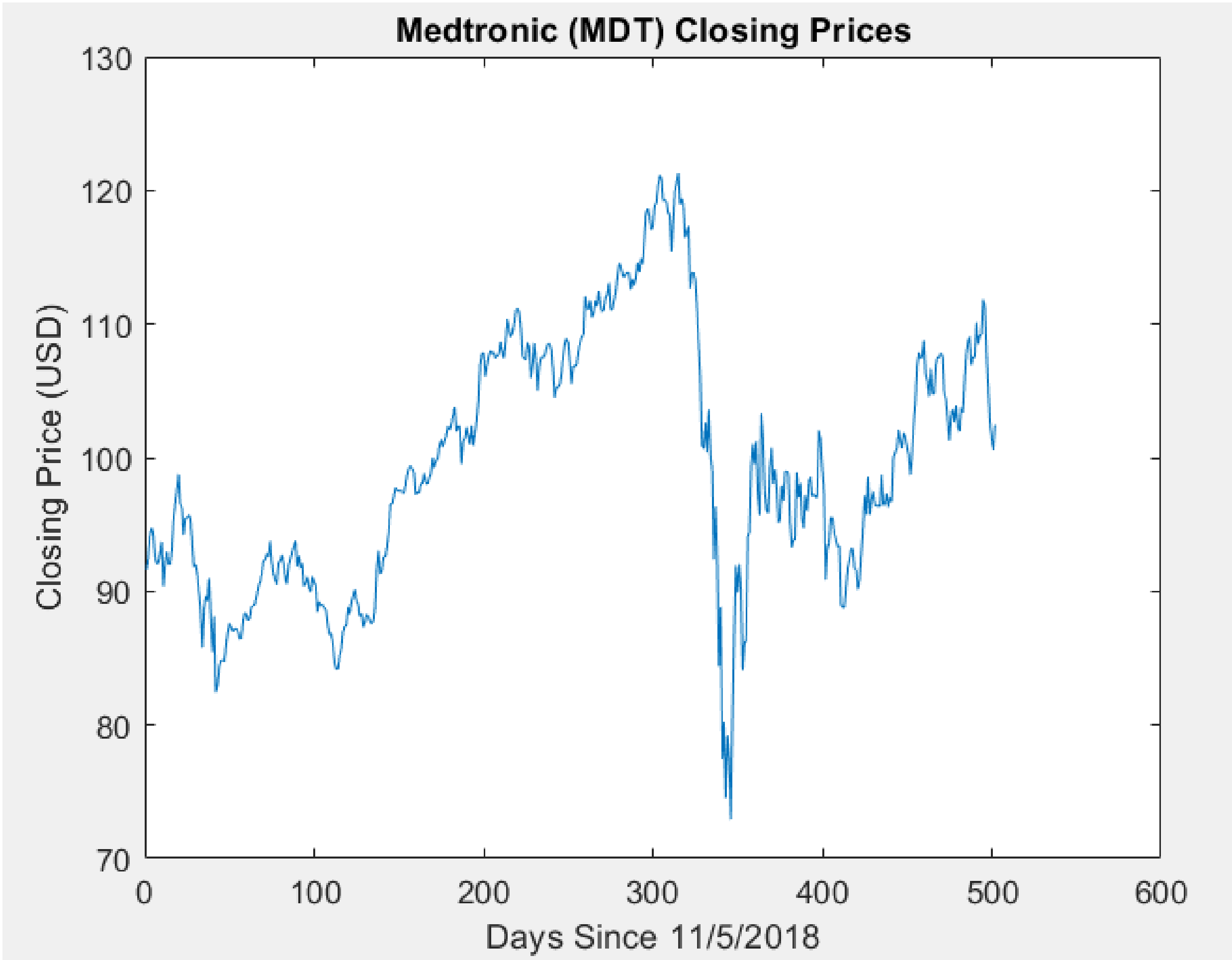

Johnson & Johnson (JNJ) Relevant Period
Closing Price (USD)
Last 178 Days
160
155
150
145
140
135
130
125
120
115
110
0
20
40
60
80
100
120
140
160
180

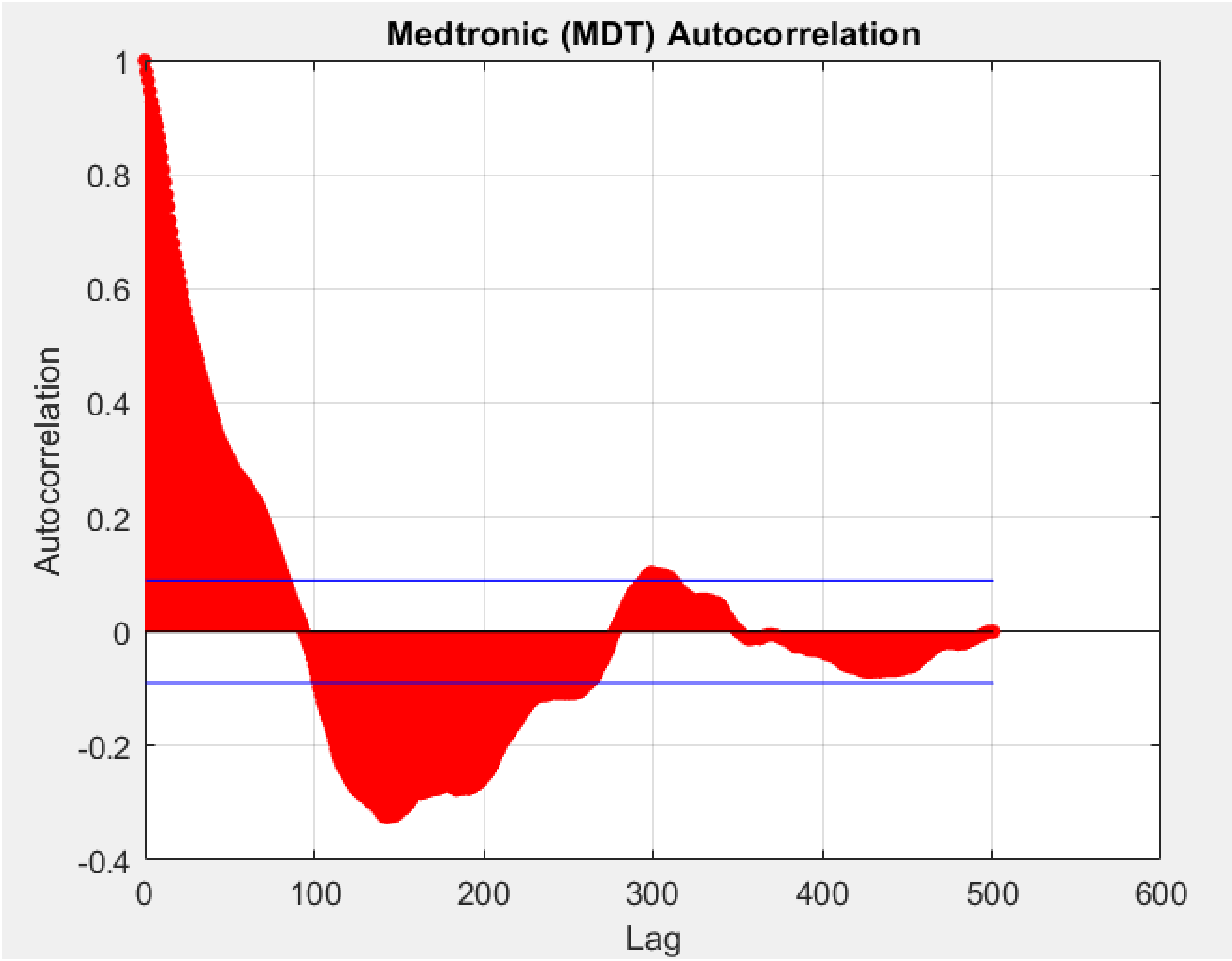

Johnson & Johnson (JNJ) Closing Price /w Trendline
Closing Price (USD)
160
155
150
145
140
135
130
125
120
115
110
0
20
40
60
80
100
120
140
160
180
Last 178 Days

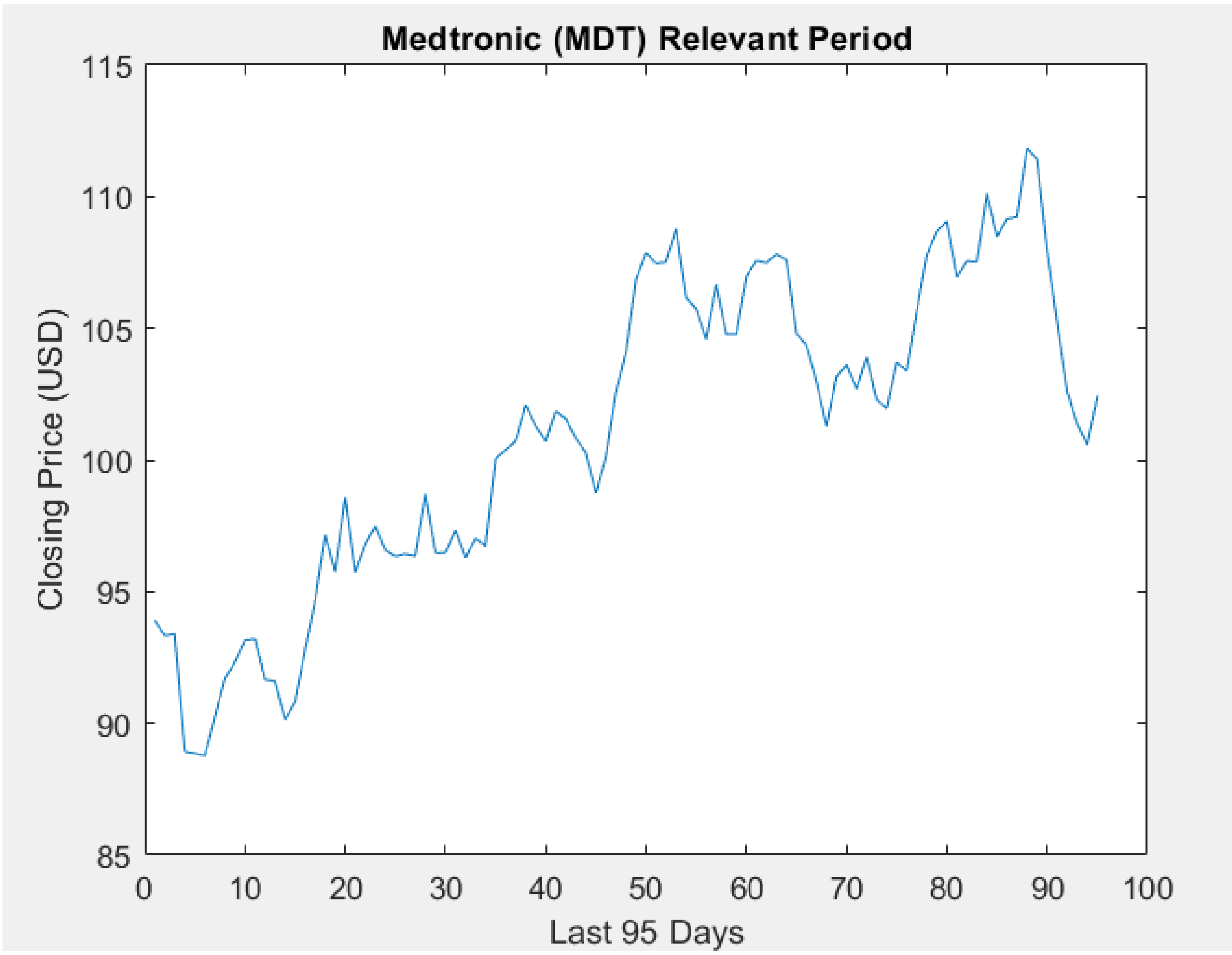

Johnson & Johnson (JNJ) Trendline Residuals
Residual (USD)
15
10
5
0
-5
-10
-15
-20
-25
-30
0
20
40
60
80
100
120
140
160
180
Last 178 Days



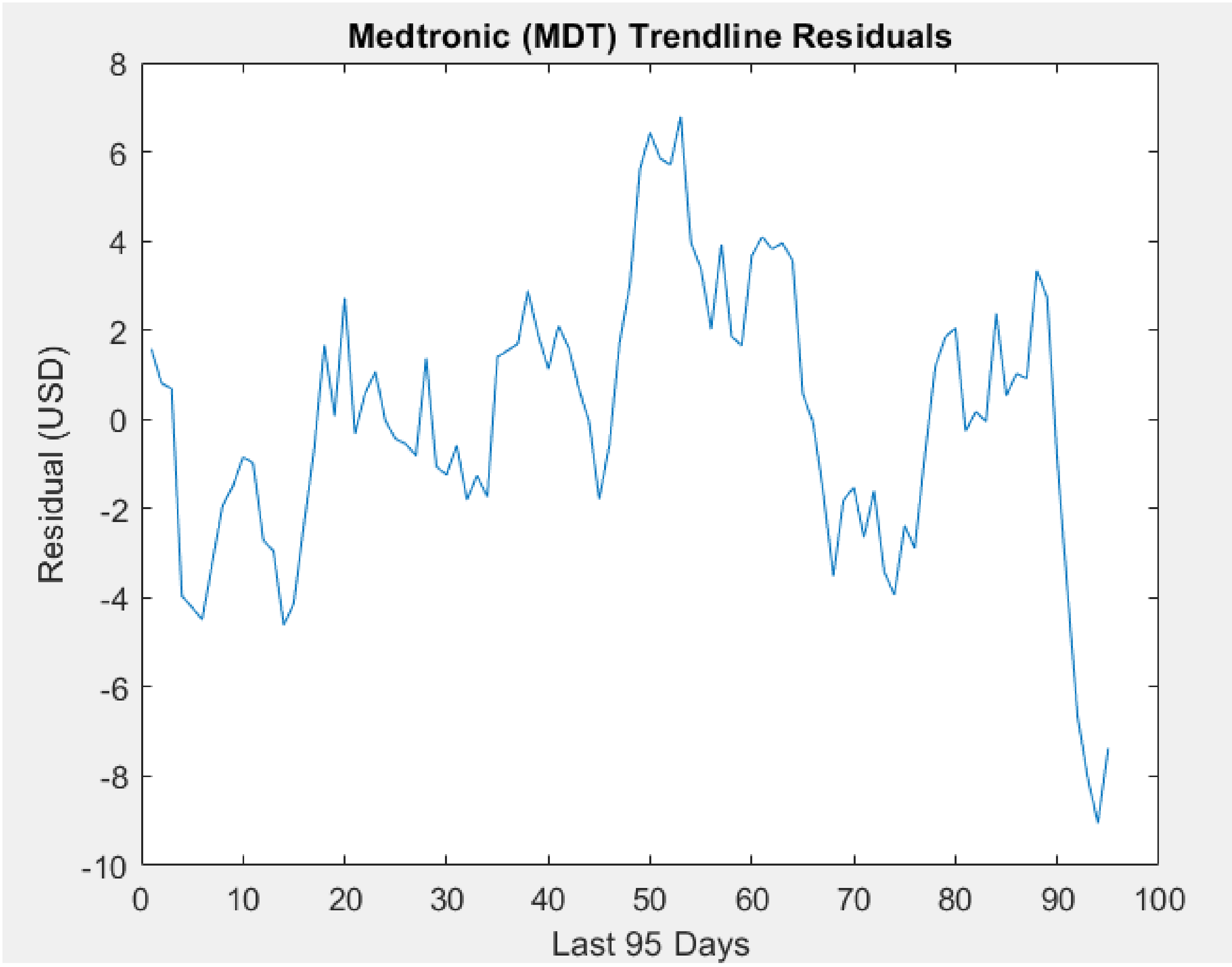
Johnson & Johnson (JNJ) Base Model
Closing Price (USD)
160
155
150
145
140
135
130
125
120
115
110
0
20
40
60
80
100
120
140
160
180
Last 178 Days

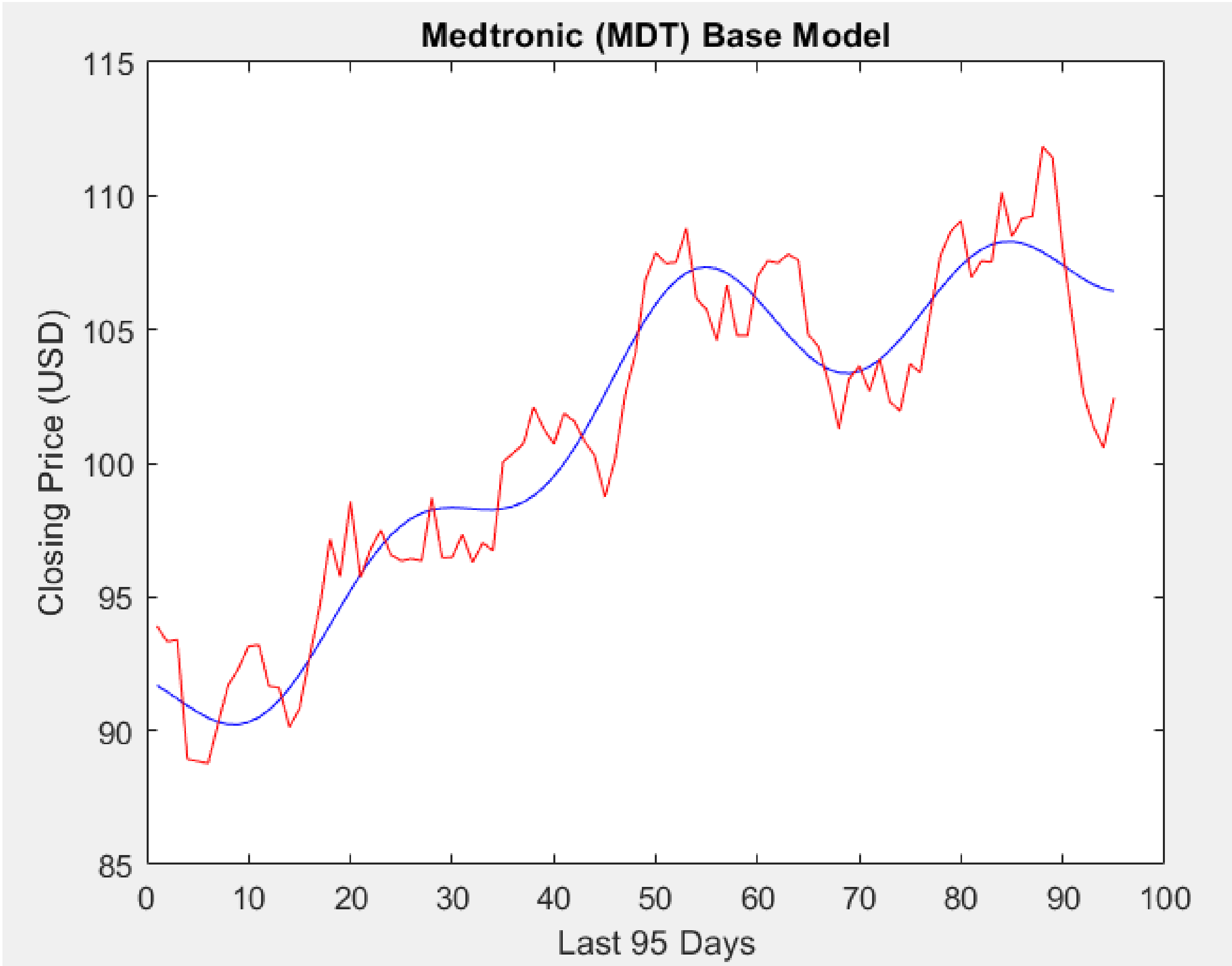

Medtronic (MDT) Closing Prices
Closing Price (USD)
Days Since 11/5/2018
130
120
110
100
90
80
70
0
100
200
300
400
500
600


Medtronic (MDT) Autocorrelation
Autocorrelation
Lag
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
100
200
300
400
500
600

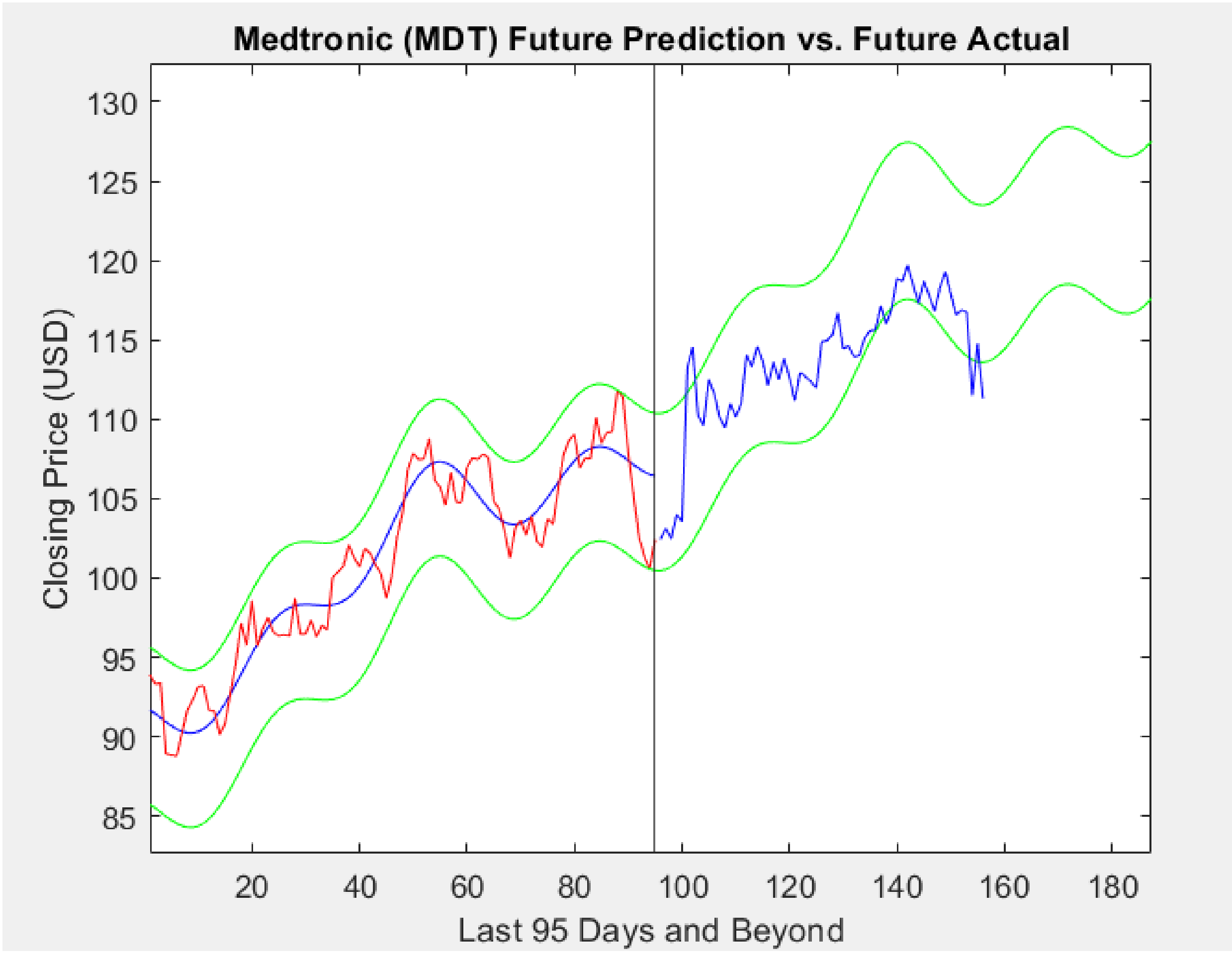

Medtronic (MDT) Relevant Period
Closing Price (USD)
115
110
105
100
95
90
85
0
10
20
30
40
50
60
70
80
90
100
Last 95 Days


Medtronic (MDT) Closing Price /w Trendline
Closing Price (USD)
115
110
105
100
95
90
85
0
10
20
30
40
50
60
70
80
90
100
Last 95 Days

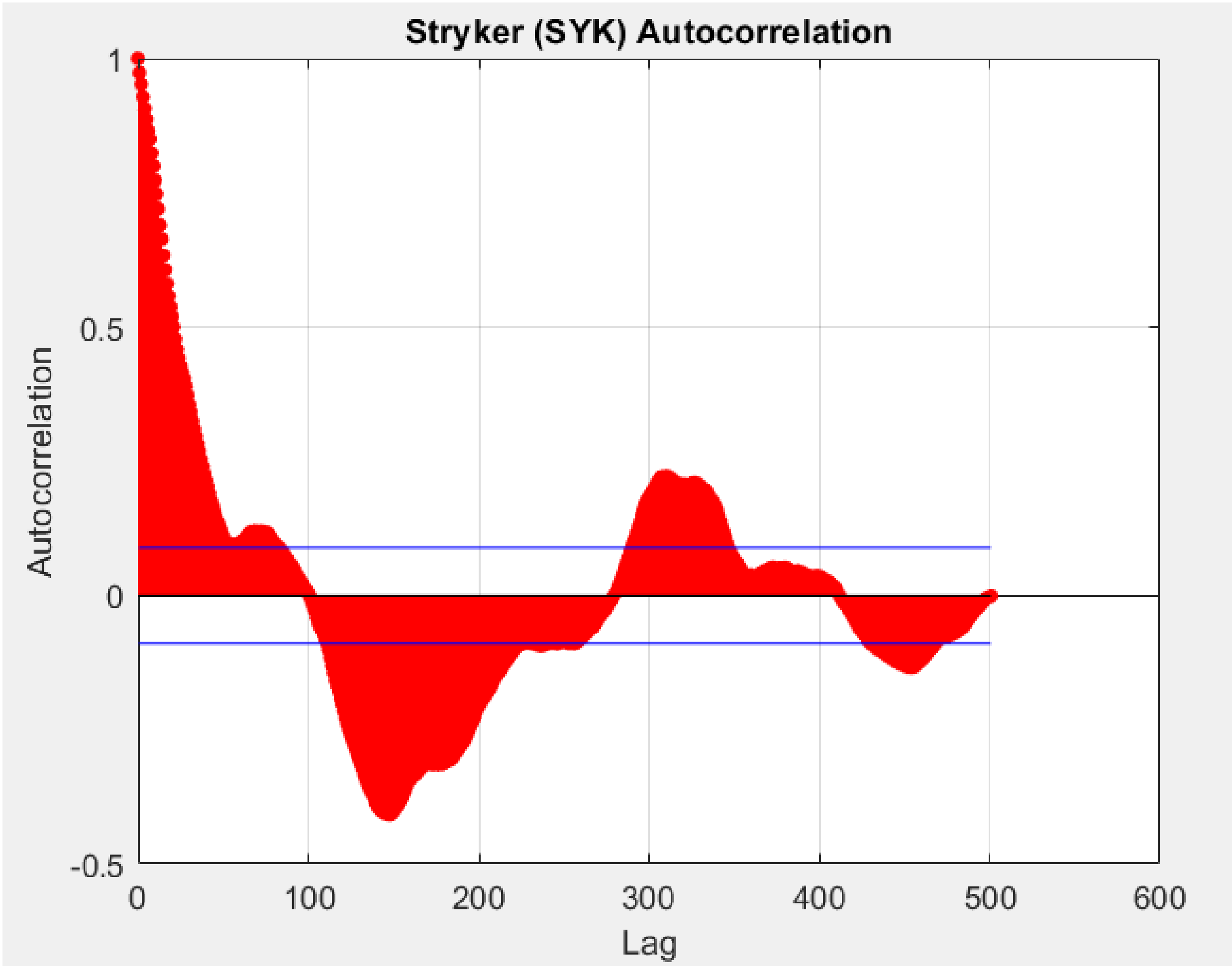

Medtronic (MDT) Trendline Residuals
Residual (USD)
8
6
4
2
0
-2
-4
-6
-8
-10
0
10
20
30
40
50
60
70
80
90
100
Last 95 Days

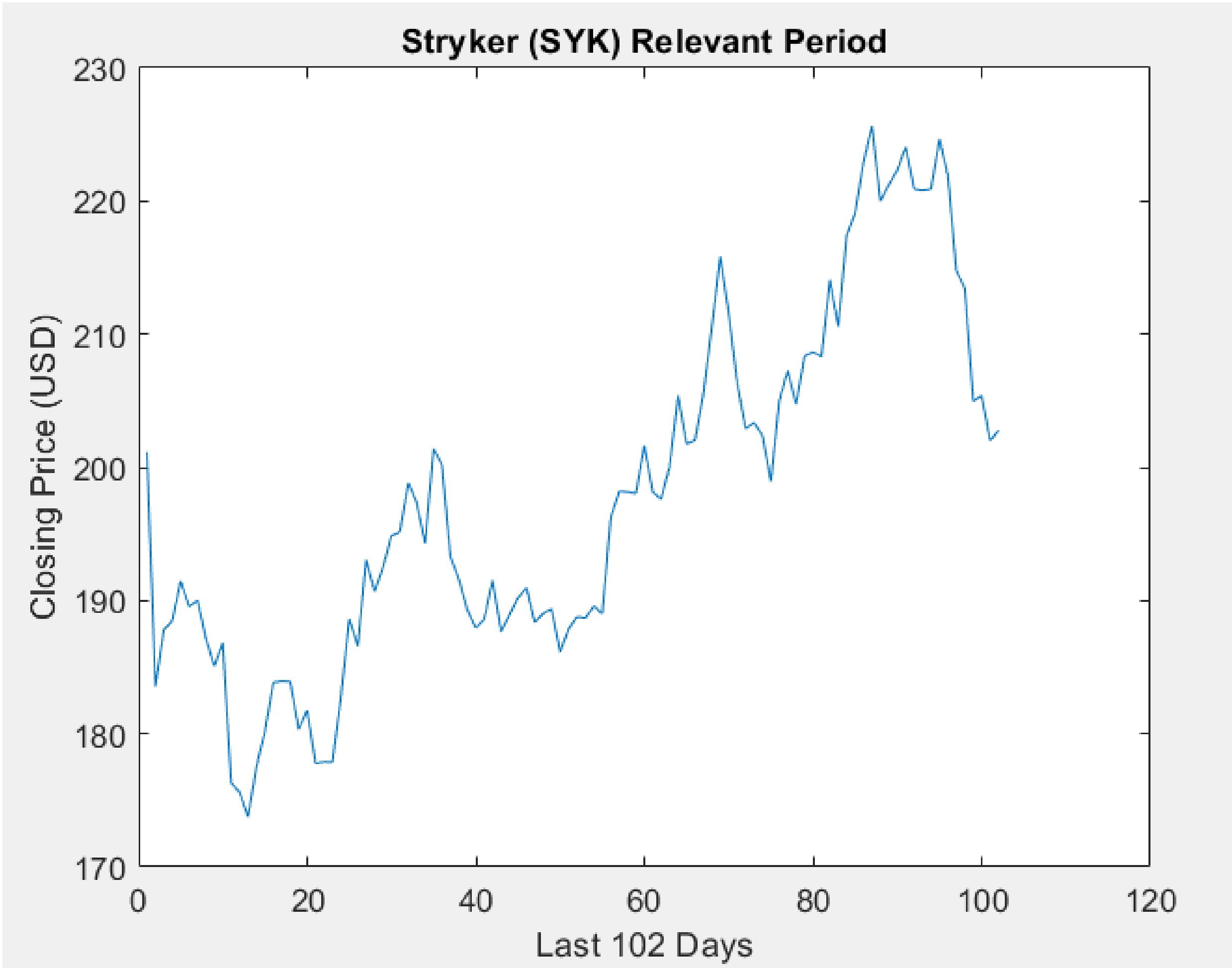


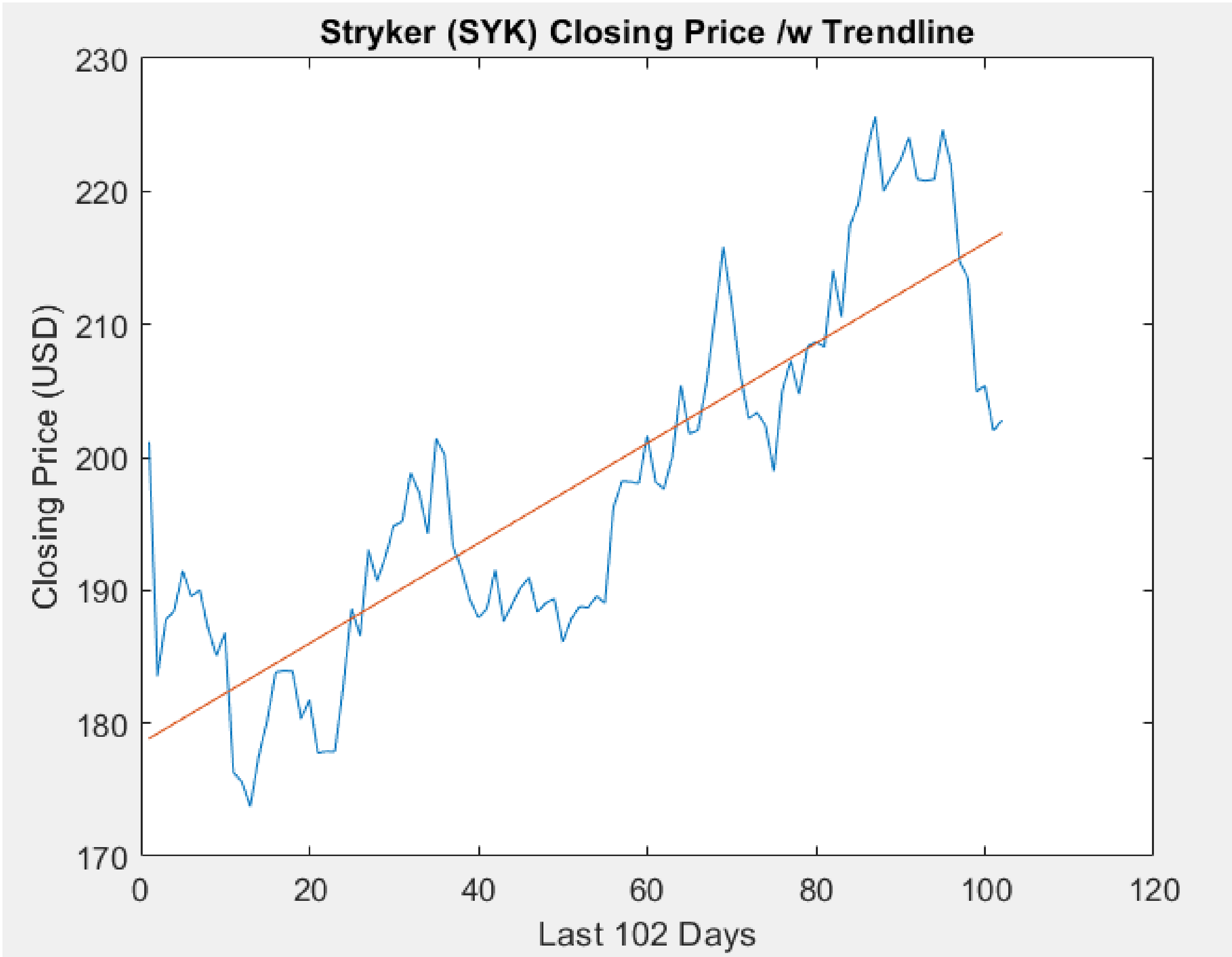
Medtronic (MDT) Base Model
Closing Price (USD)
Last 95 Days
115
110
105
100
95
90
85
0
10
20
30
40
50
60
70
80
90
100

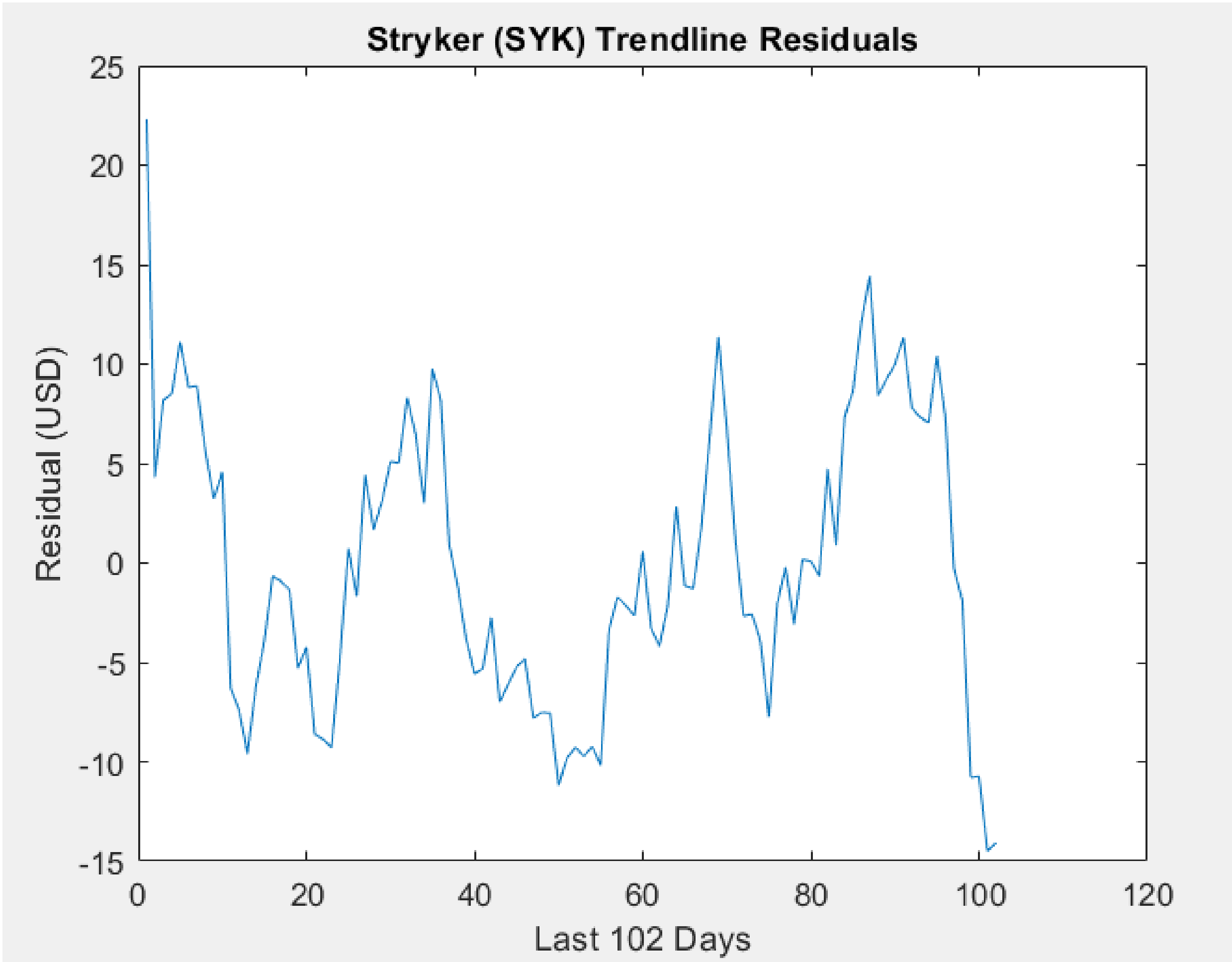

Medtronic (MDT) Future Prediction vs. Future Actual
Closing Price (USD)
130
125
120
115
110
105
100
95
90
85
20
40
60
80
100
120
140
160
180
Last 95 Days and Beyond

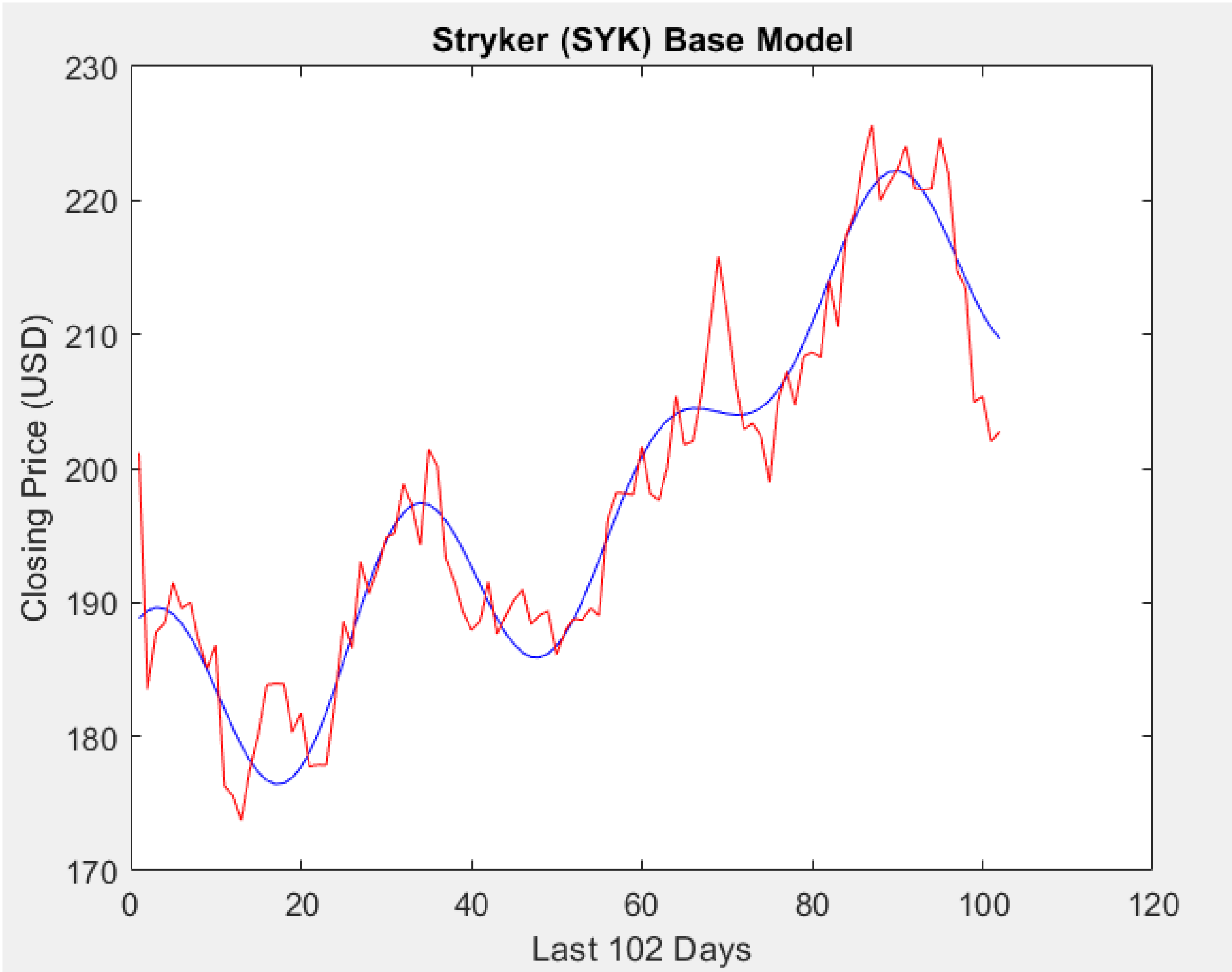

Stryker (SYK) Closing Prices
Closing Price (USD)
240
220
200
180
160
140
120
0
100
200
300
400
500
600
Days Since 11/5/2018

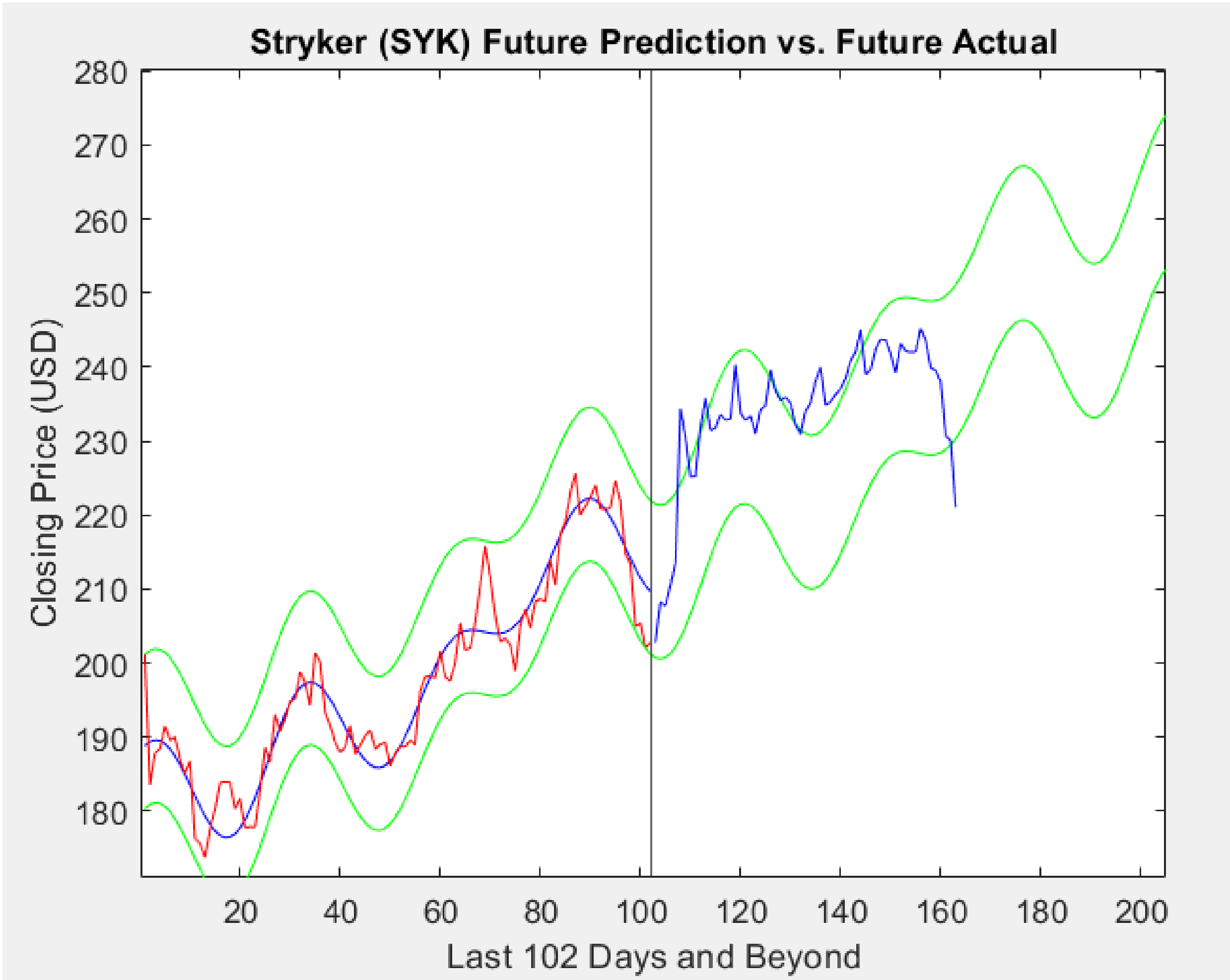

Stryker (SYK) Autocorrelation
1
0.5
0
-0.5
Autocorrelation
0
100
200
300
400
500
600
Lag


Stryker (SYK) Relevant Period
Closing Price (USD)
Last 102 Days
230
220
210
200
190
180
170
0
20
40
60
80
100
120

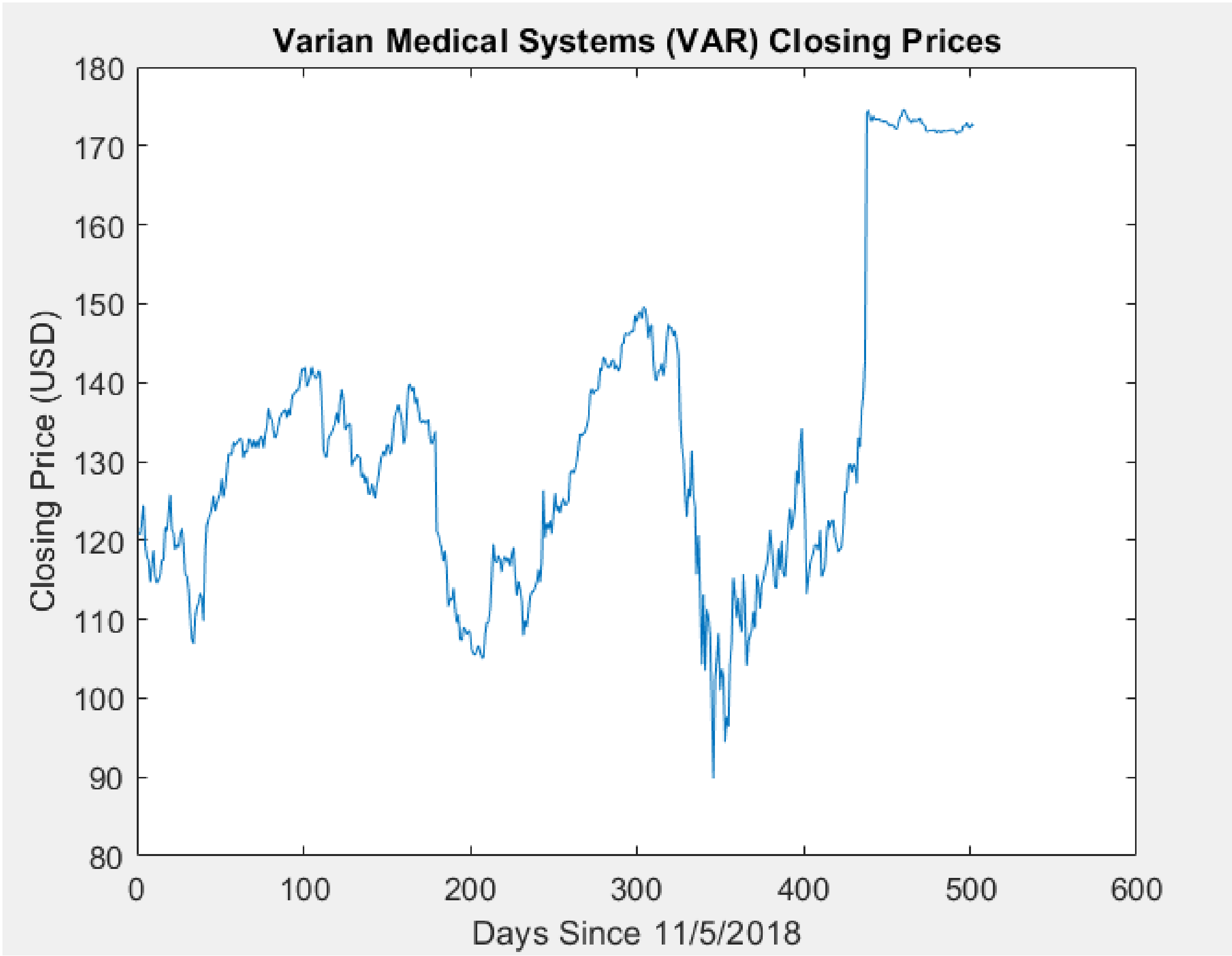

Stryker (SYK) Closing Price /w Trendline
Closing Price (USD)
Last 102 Days
230
220
210
200
190
180
170
0
20
40
60
80
100
120


Stryker (SYK) Trendline Residuals
Residual (USD)
25
20
15
10
5
0
-5
-10
-15
0
20
40
60
80
100
120
Last 102 Days

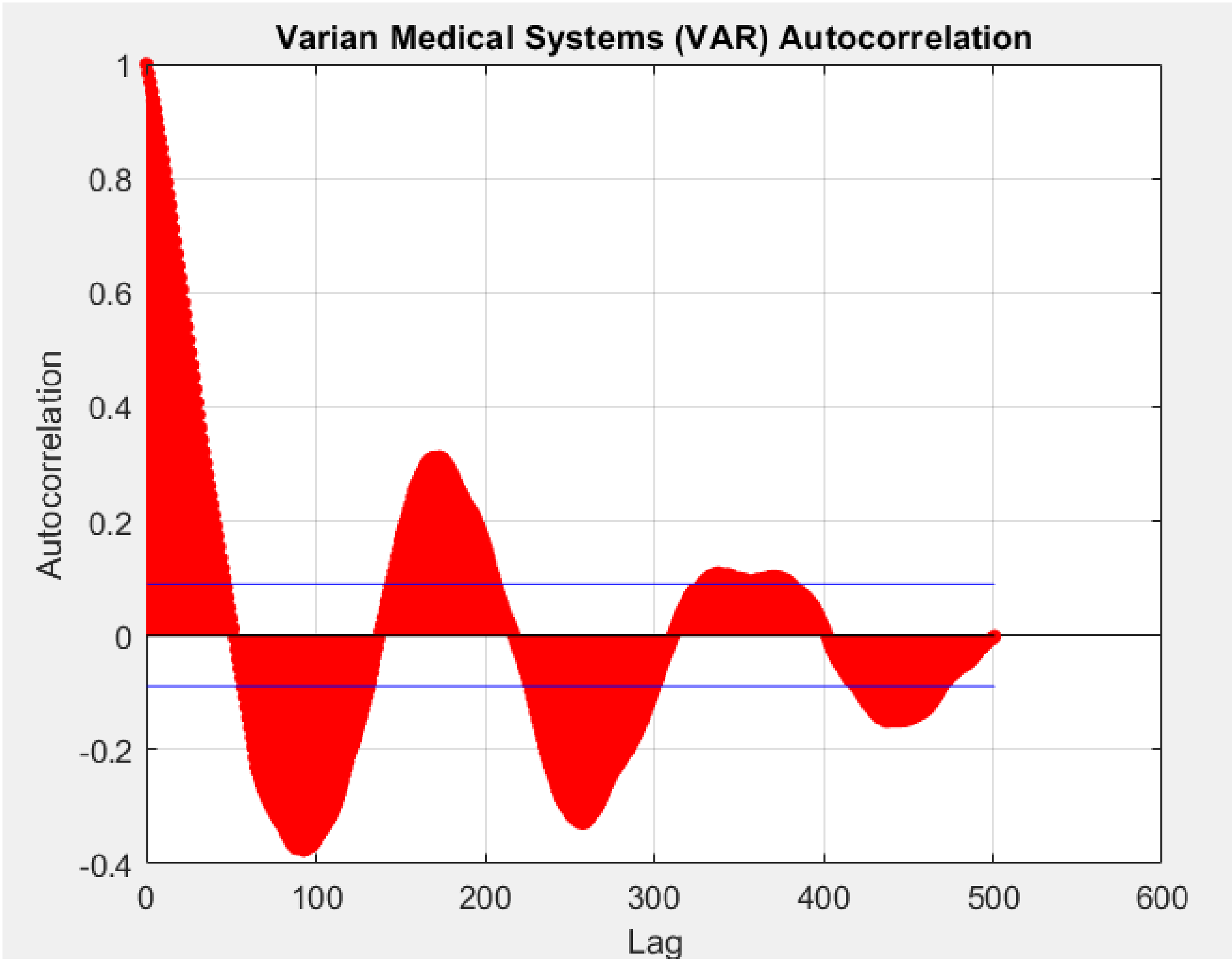

Stryker (SYK) Base Model
230
220
210
200
190
180
170
Closing Price (USD)
0
20
40
60
80
100
120
Last 102 Days

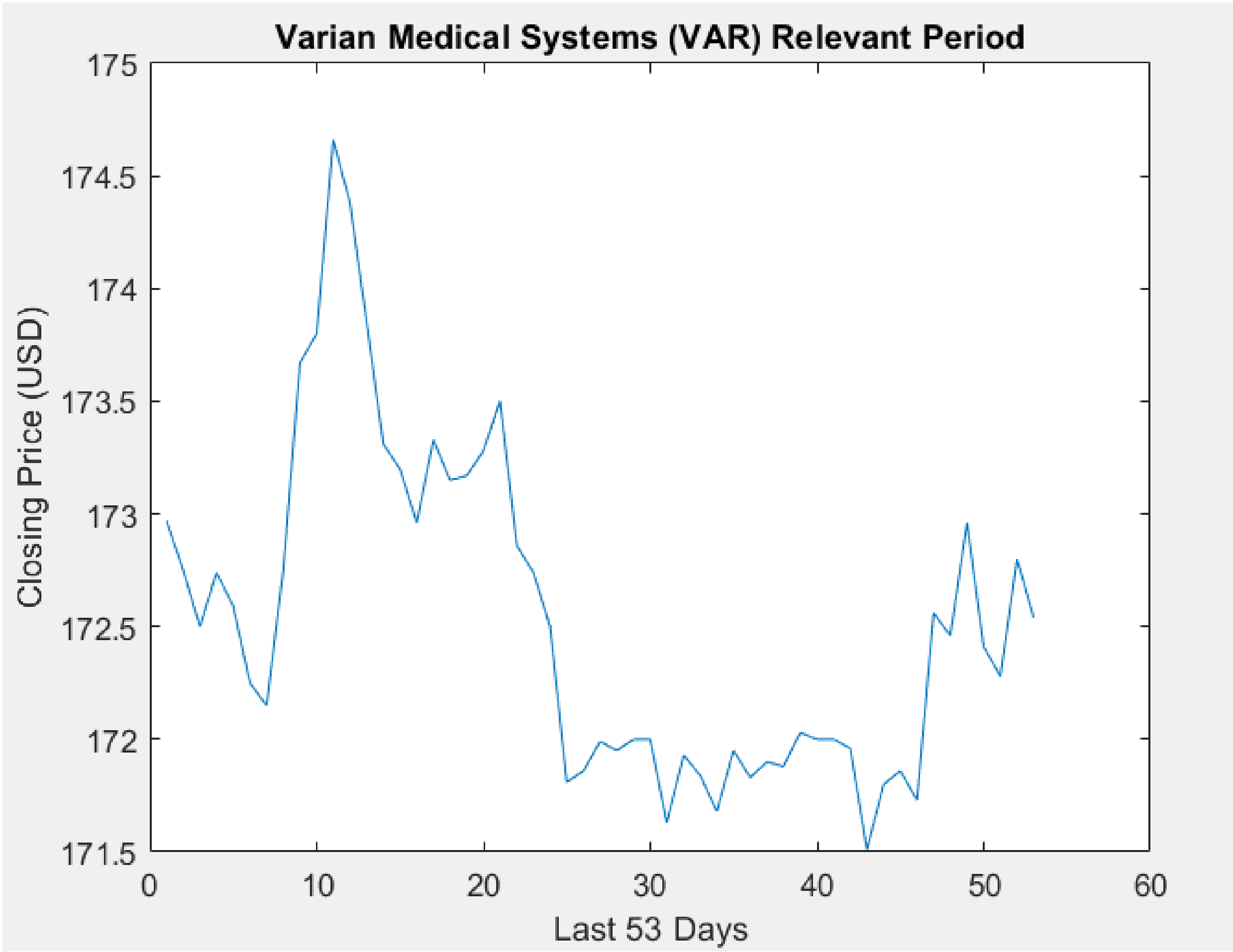


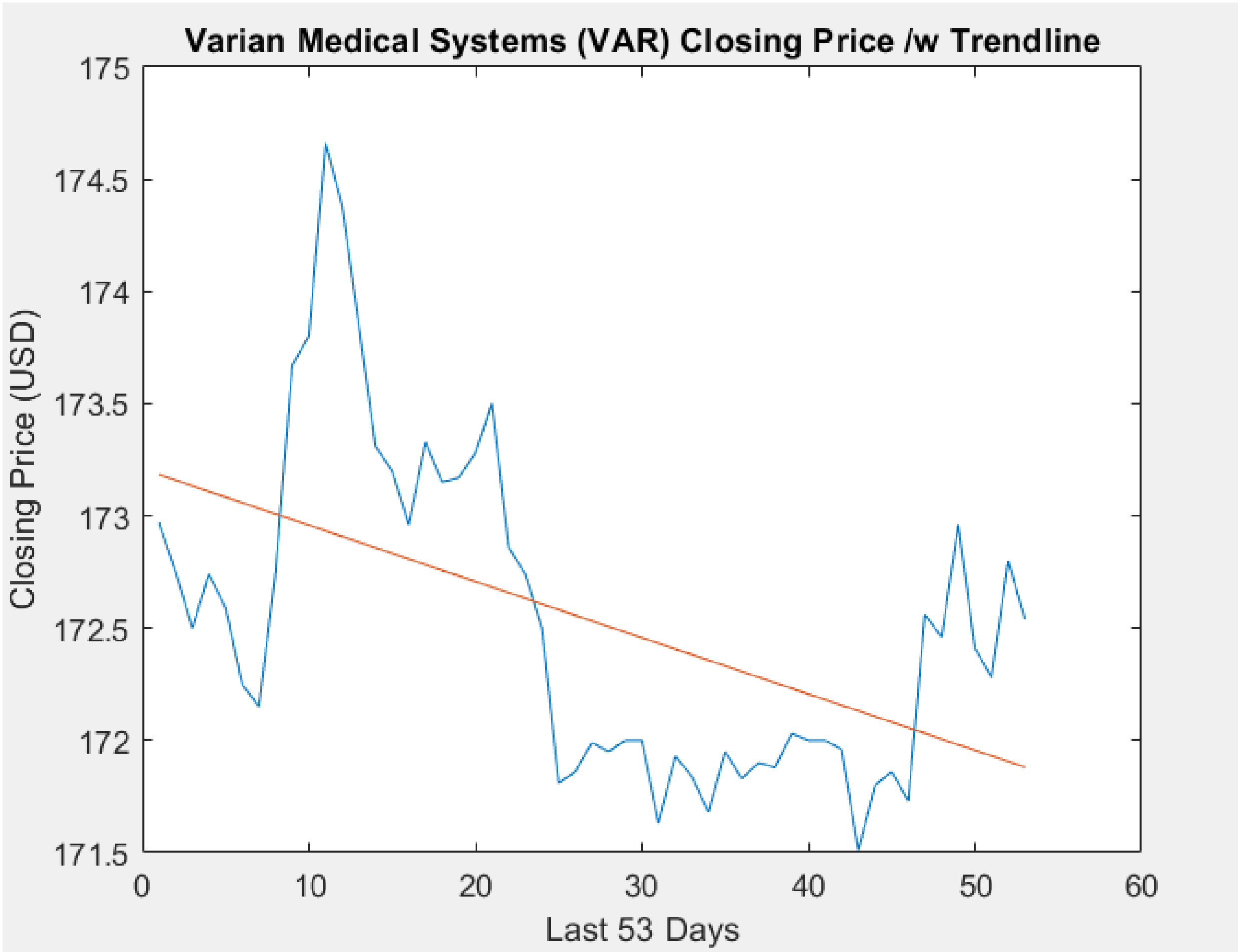
Stryker (SYK) Future Prediction vs. Future Actual
Closing Price (USD)
280
270
260
250
240
230
220
210
200
190
180
20
40
60
80
100
120
140
160
180
200
Last 102 Days and Beyond

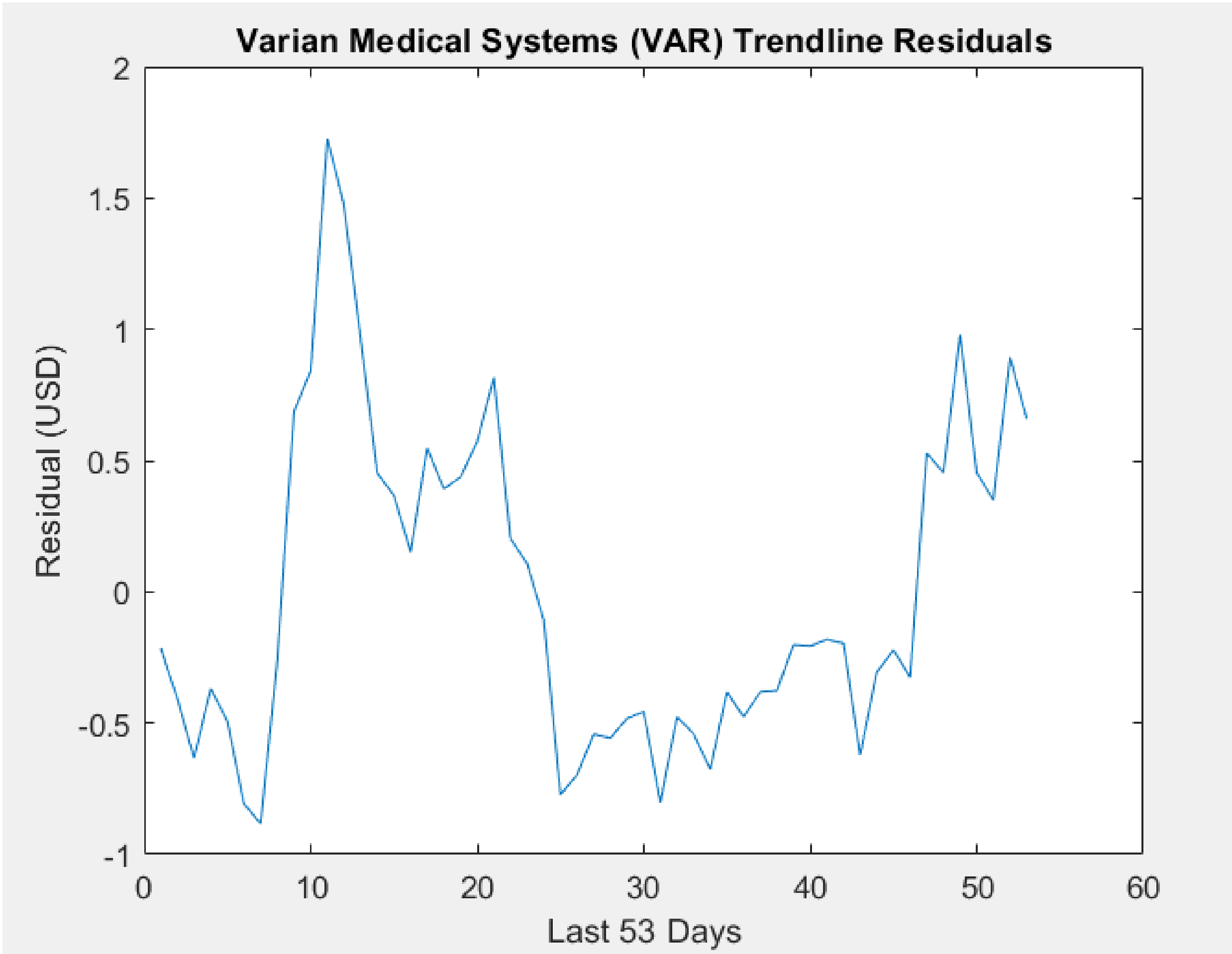


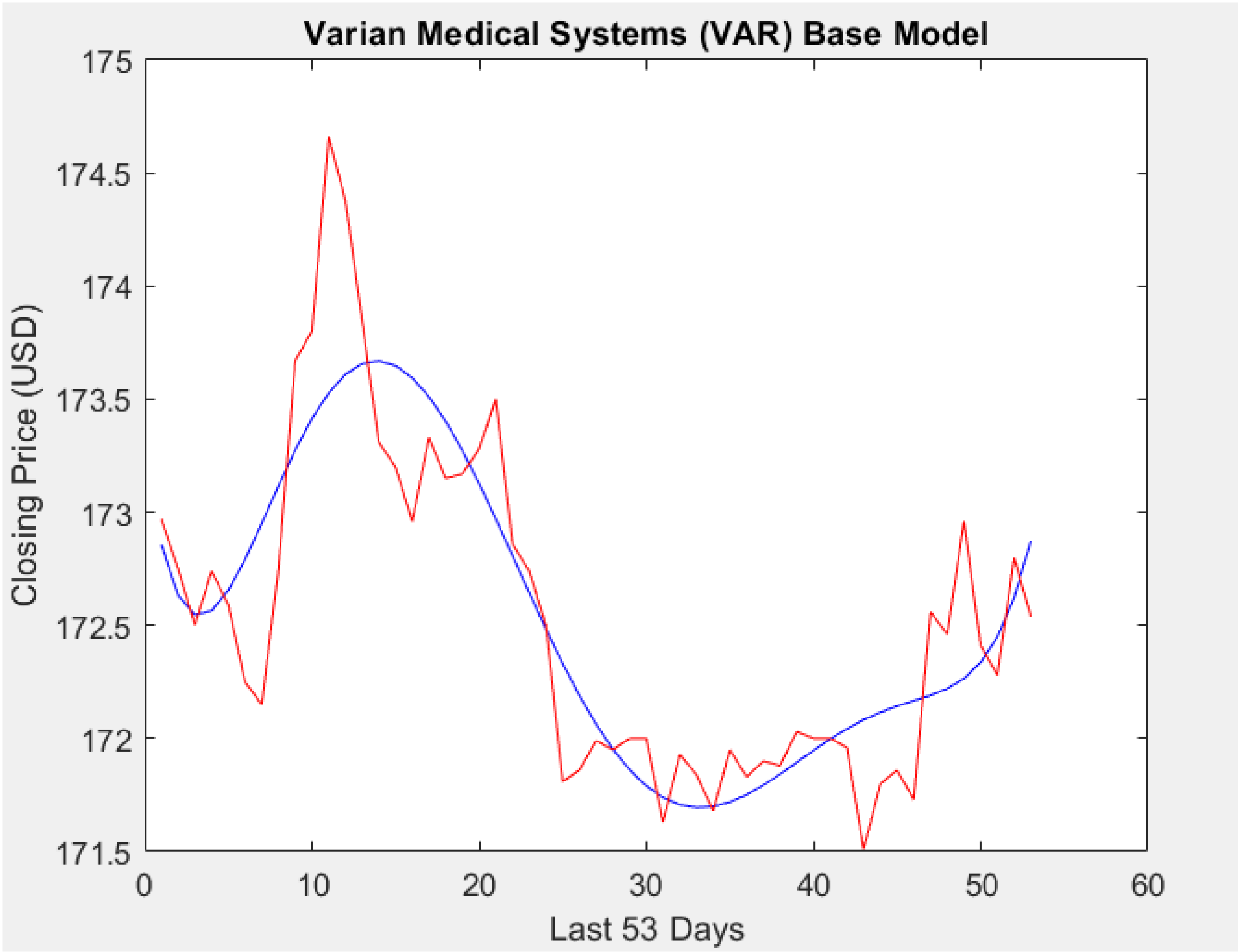
Varian Medical Systems (VAR) Closing Prices
Closing Price (USD)
180
170
160
150
140
130
120
110
100
90
80
0
100
200
300
400
500
600
Days Since 11/5/2018

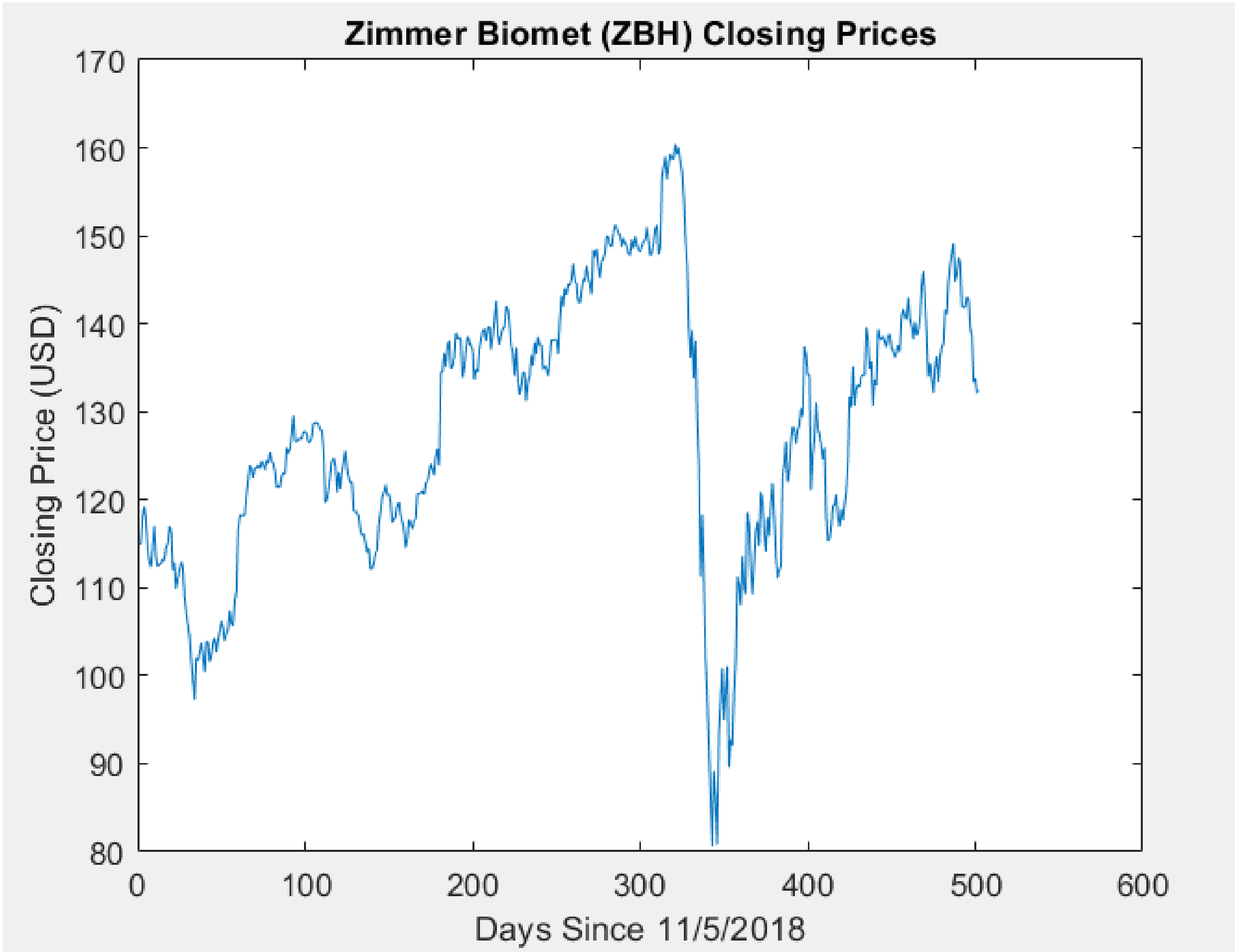

Varian Medical Systems (VAR) Autocorrelation
Autocorrelation
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
100
200
300
400
500
600
Lag

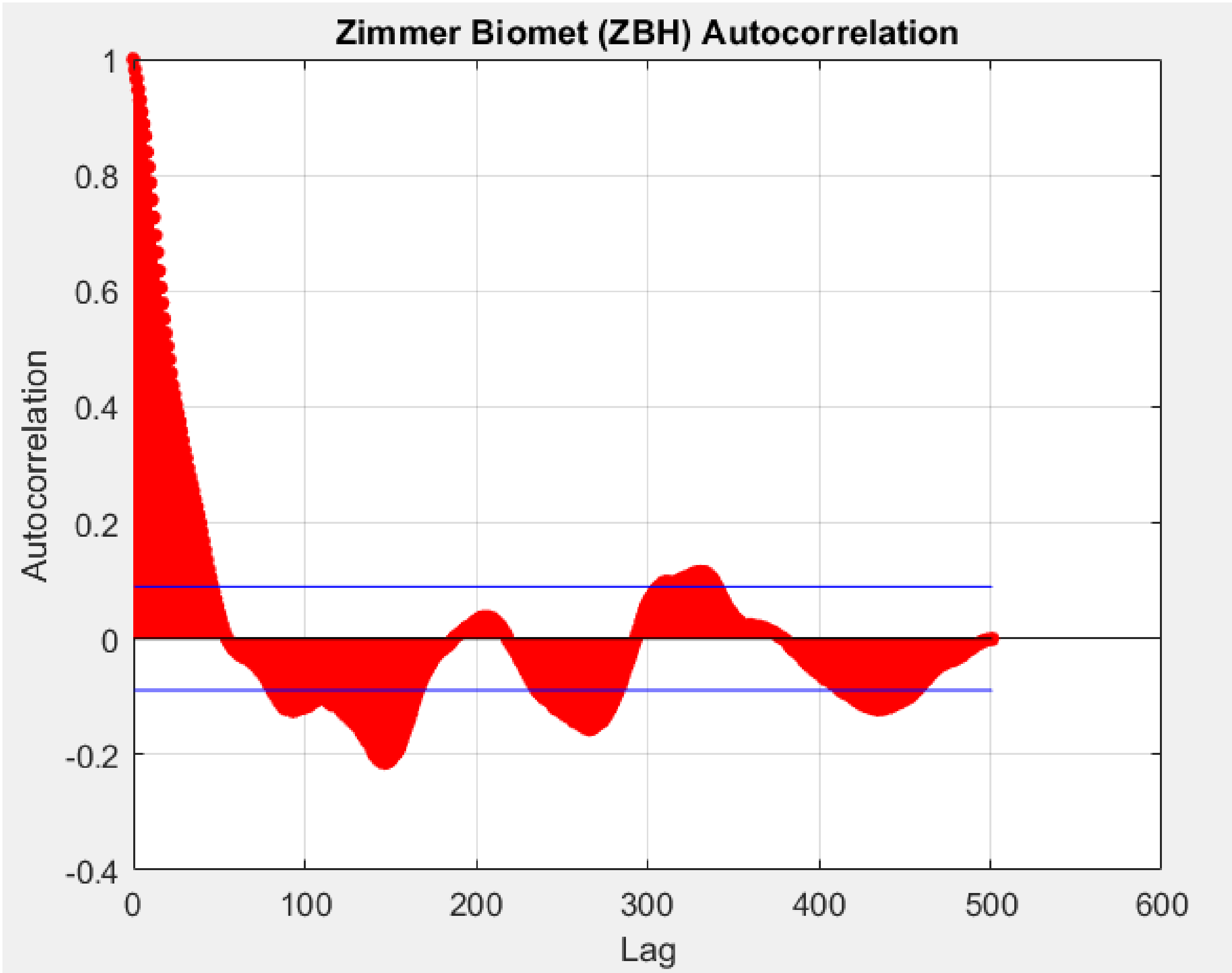

Varian Medical Systems (VAR) Relevant Period
Closing Price (USD)
175
174.5
174
173.5
173
172.5
172
171.5
0
10
20
30
40
50
60
Last 53 Days

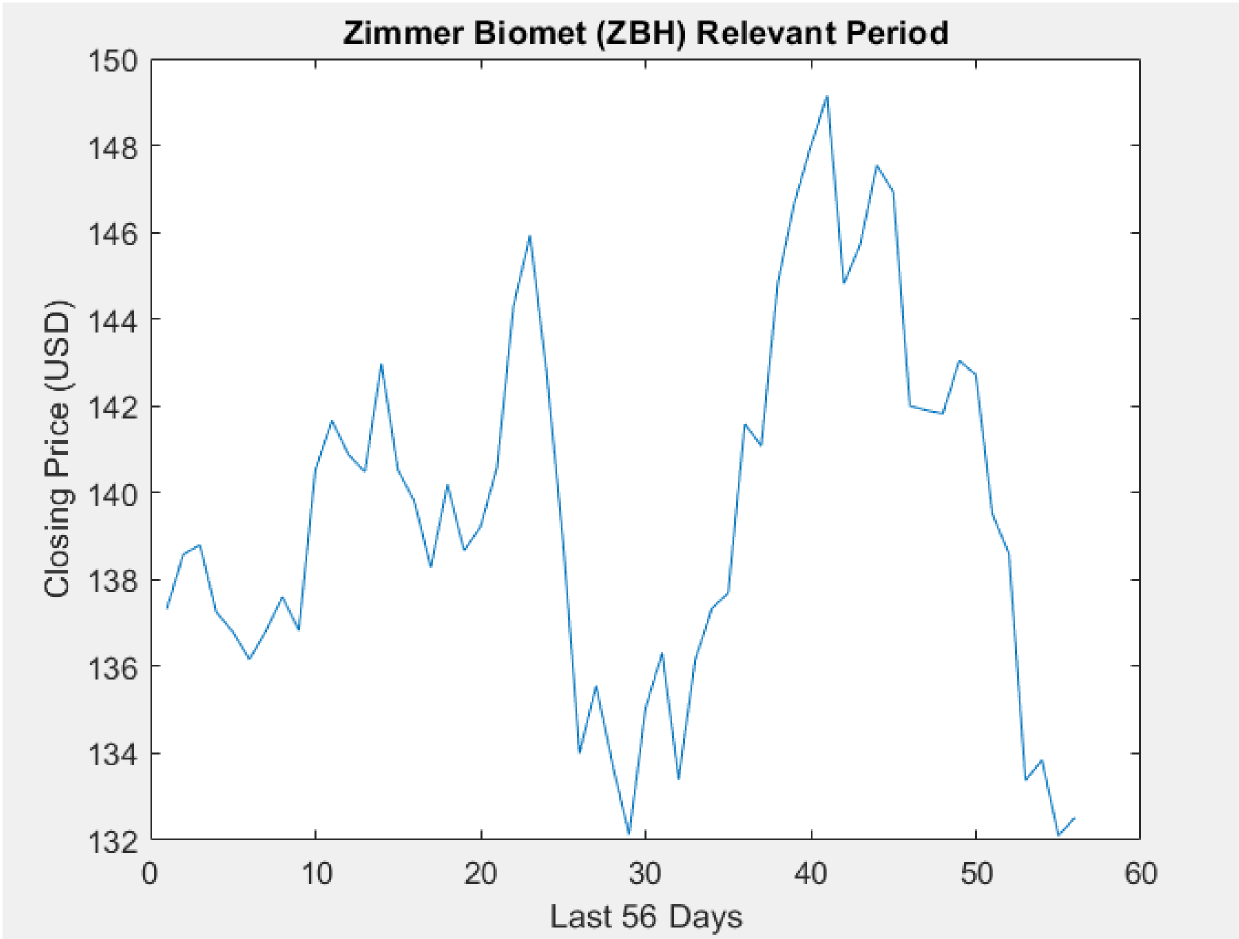

Varian Medical Systems (VAR) Closing Price /w Trendline
175
174.5
174
173.5
173
172.5
172
171.5
Closing Price (USD)
0
10
20
30
40
50
60
Last 53 Days

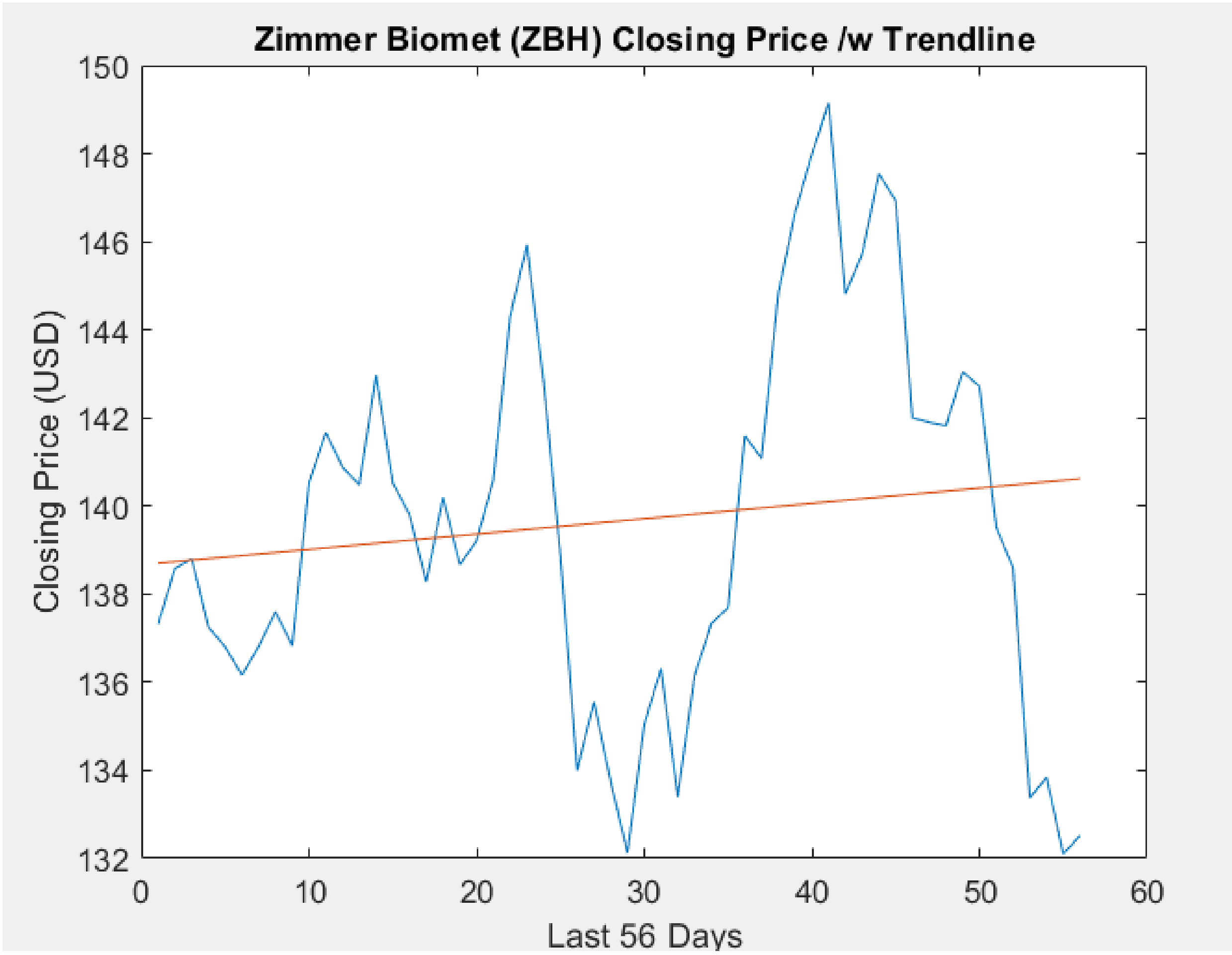

Varian Medical Systems (VAR) Trendline Residuals
Residual (USD)
Last 53 Days
2
1.5
1
0.5
0
-0.5
-1
0
10
20
30
40
50
60

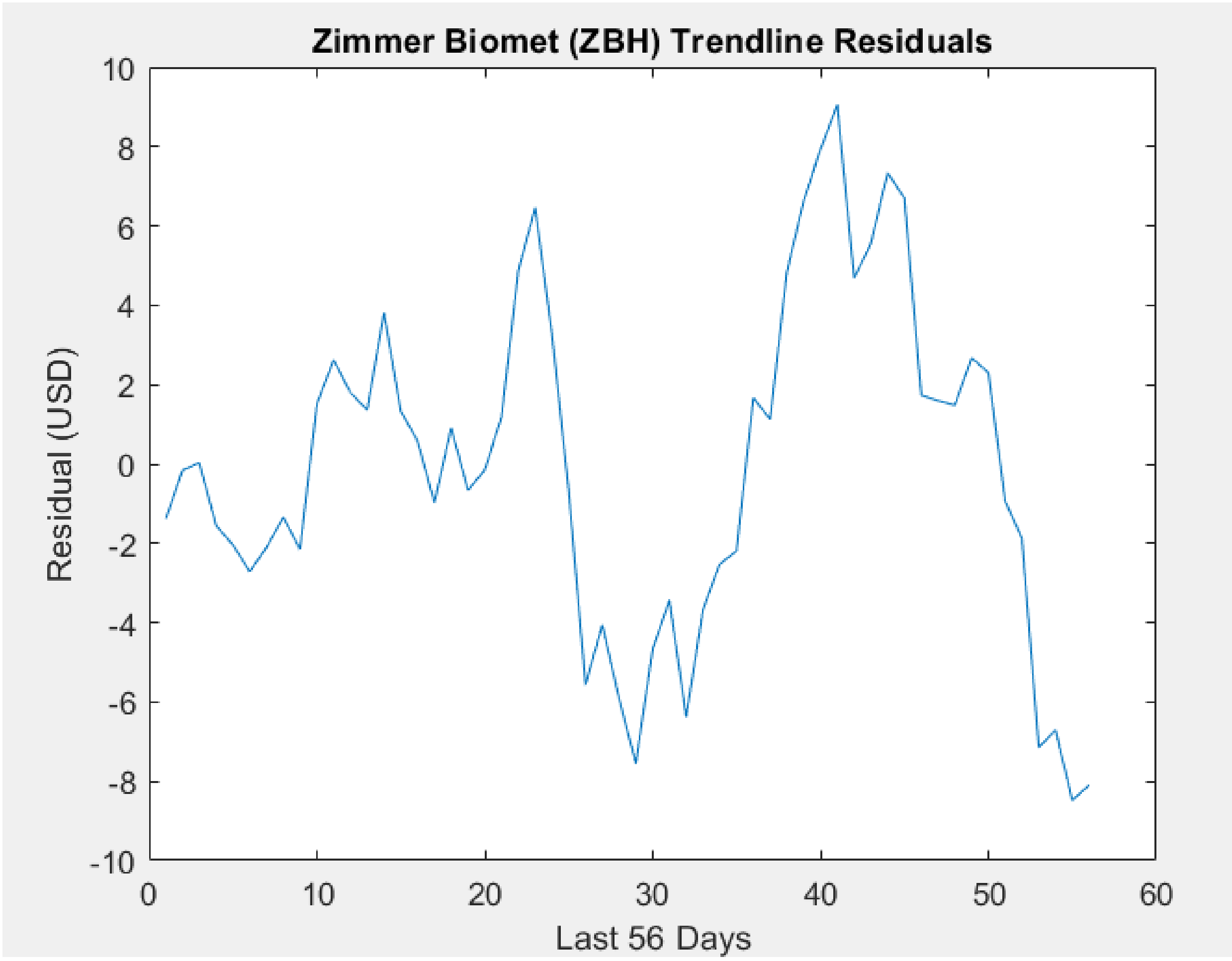

Varian Medical Systems (VAR) Base Model
175
174.5
174
173.5
173
172.5
172
171.5
0
10
20
30
40
50
60
Closing Price (USD)
Last 53 Days

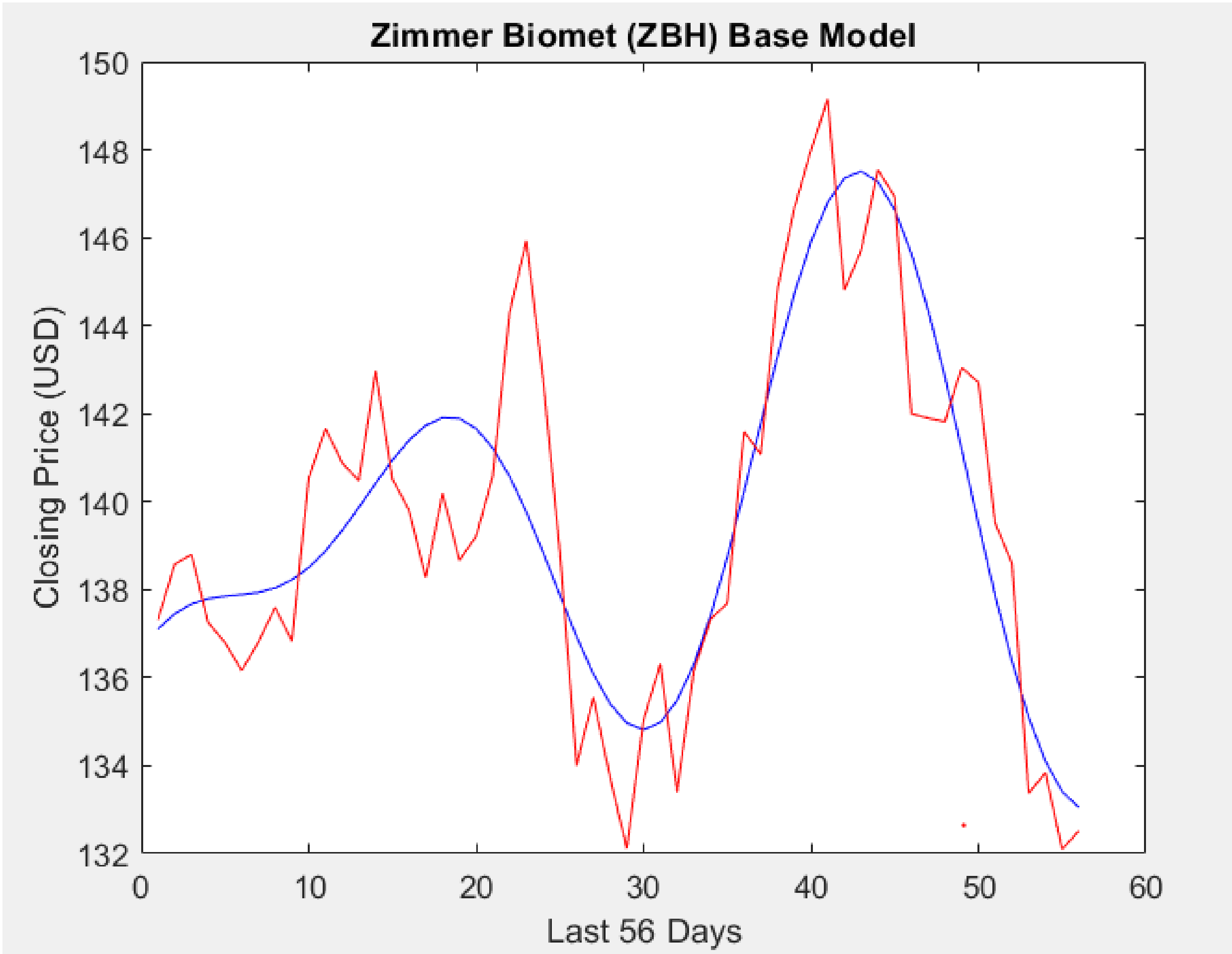

Zimmer Biomet (ZBH) Closing Prices
Closing Price (USD)
170
160
150
140
130
120
110
100
90
80
0
100
200
300
400
500
600
Days Since 11/5/2018


Zimmer Biomet (ZBH) Autocorrelation
Autocorrelation
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0
100
200
300
400
500
600
Lag

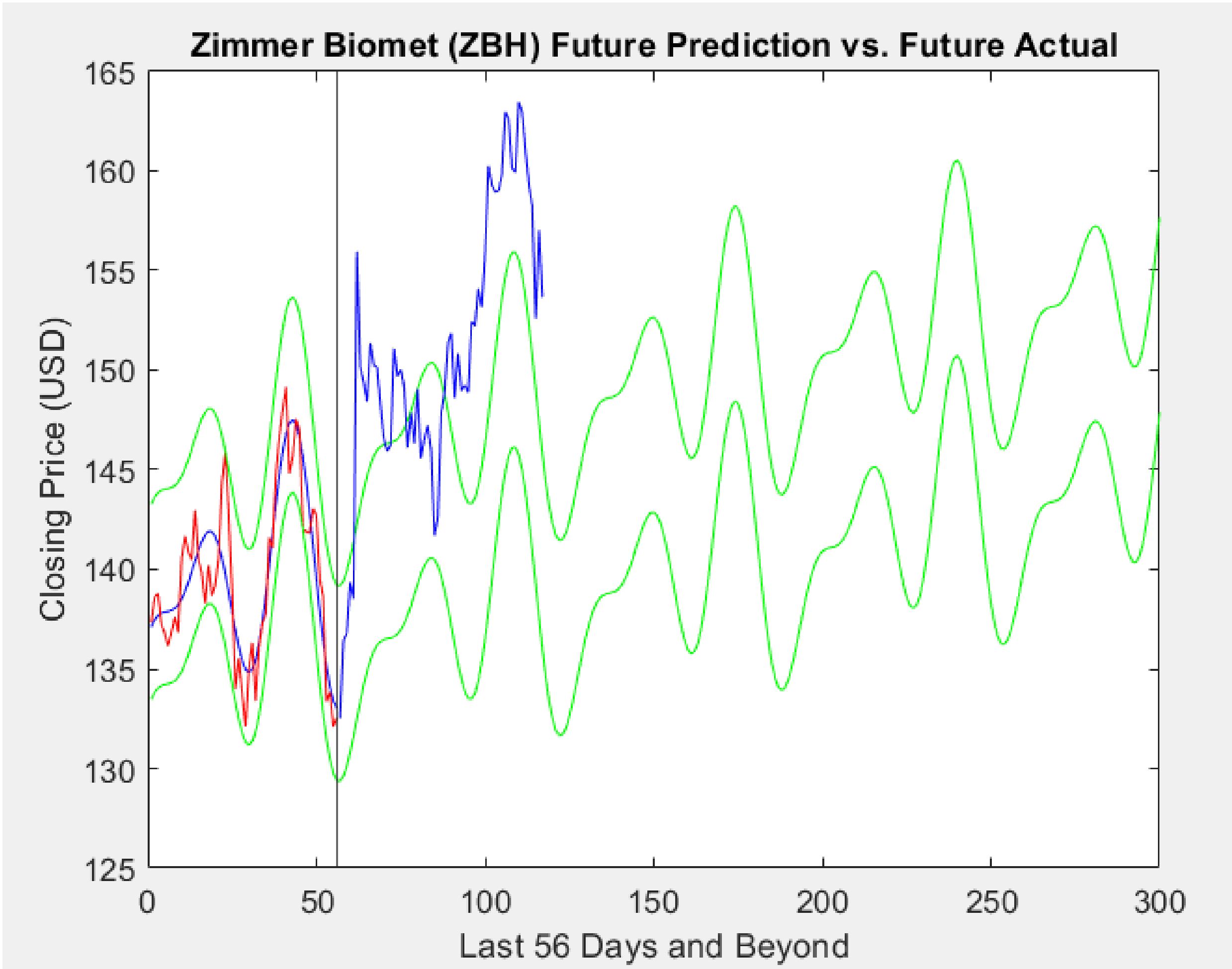

Zimmer Biomet (ZBH) Relevant Period
Closing Price (USD)
150
148
146
144
142
140
138
136
134
132
0
10
20
30
40
50
60
Last 56 Days


Zimmer Biomet (ZBH) Closing Price /w Trendline
150
148
146
144
142
140
138
136
134
132
Closing Price (USD)
0
10
20
30
40
50
60
Last 56 Days


Zimmer Biomet (ZBH) Trendline Residuals
Residual (USD)
Last 56 Days
10
8
6
4
2
0
-2
-4
-6
-8
-10
0
10
20
30
40
50
60



Zimmer Biomet (ZBH) Base Model
Closing Price (USD)
150
148
146
144
142
140
138
136
134
132
0
10
20
30
40
50
60
Last 56 Days



Base Model:

```
load ('BDX.csv')

prclose=BDX(:,5);

name="Becton Dickinson (BDX)";

aa="27";

a=27;

for i=1:502

    data(i)=prclose(503-i);

    historical(i)=prclose(i);
```

```
end
load ('BDXfuture.csv')
prfuture=BDXfuture(:,5);
for i=1:61
   fut(i)=prfuture(i);
end
jj=linspace(a+1,a+61,61);
xx=linspace(1,502,502);
plot(xx,historical)
title(name + ' Closing Prices')
xlabel('Days Since 11/5/2018')
ylabel('Closing Price (USD)')
pause
autocorr(data,501)
title(name + ' Autocorrelation')
xlabel('Lag')
ylabel('Autocorrelation')
pause
RV=prclose(503-a:502);
yy=linspace(1,a,a);
plot(yy,RV)
title(name + ' Relevant Period')
```

```
xlabel('Last '+aa+' Days')

ylabel('Closing Price (USD)')

hold

pause

p=polyfit(yy,transpose(RV),1)

for i=1:a

trend(i)=p(1)*i+p(2);

end

[n,m]=size(yy)

[n,m]=size(trend)

plot(yy,trend)

title(name + ' Closing Price /w Trendline')

xlabel('Last '+aa+' Days')

ylabel('Closing Price (USD)')

hold

pause

prdiff=transpose(RV)-trend;

plot(yy,prdiff)

title(name + ' Trendline Residuals')

xlabel('Last '+aa+' Days')

ylabel('Residual (USD)')

pause
```

```
f=fit(yy',prdiff','fourier3'); %f will have the coeff of the fourier expansion
for i=1:a
yh(i)=trend(i)+f(i);
end
plot(yy,yh,'b')
hold
plot(yy,RV,'r')
title(name + ' Base Model')
xlabel('Last '+aa+' Days')
ylabel('Closing Price (USD)')
pause
prdiff2=transpose(RV)-yh;
%plot(yy,prdiff2)%
zz=linspace(1,300,300);
for x=1:300
prd(x)=p(1)*x+p(2)+f(x);
end
%plot(zz,prd)
plot(zz,prd+max(prdiff2),'g')
plot(zz,prd+min(prdiff2),'g')
plot(jj,fut,'b')
title(name + ' Future Prediction vs. Future Actual')
```

```
xlabel('Last '+aa+' Days and Beyond')

ylabel('Closing Price (USD)')

xline(a)

hold
```

Moving Averages Model:

```
load ('BDX.csv')

prclose=BDX(:,5);

[n,m]=size(BDX(:,5))

tend=n

for i=10:tend-10

az=0;

for j=1:20

az=az+prclose(i+j-10);

end

prsmooth(i)=az/20;

end

%since you are not smoothing the fist 10 nine ponts andthe last 10

%use the original data for these points

for i=1:10

prsmooth(i)=prclose(i);

prsmooth(tend-i+1)=prclose(tend-i+1);

end

plot(prsmooth)

pause

name="Becton Dickinson (BDX)";

aa="27";
```

```
a=27;
for i=1:502
    data(i)=prsmooth(503-i);
    historical(i)=prsmooth(i);
end
load ('BDXfuture.csv')
prfuture=BDXfuture(:,5);
for i=1:61
    fut(i)=prfuture(i);
end
jj=linspace(a+1,a+61,61);
xx=linspace(1,502,502);
plot(xx,historical)
title(name + ' Closing Prices')
xlabel('Days Since 11/5/2018')
ylabel('Closing Price (USD)')
pause
autocorr(data,501)
title(name + ' Autocorrelation')
xlabel('Lag')
ylabel('Autocorrelation')
pause
```

```
RV=prsmooth(503-a:502);

yy=linspace(1,a,a);

plot(yy,RV)

title(name + ' Relevant Period')

xlabel('Last '+aa+' Days')

ylabel('Closing Price (USD)')

hold

pause

p=polyfit(yy,(RV),1)

for i=1:a

trend(i)=p(1)*i+p(2);

end

plot(yy,trend)

title(name + ' Closing Price /w Trendline')

xlabel('Last '+aa+' Days')

ylabel('Closing Price (USD)')

hold

pause

prdiff=(RV)-trend;

plot(yy,prdiff)

title(name + ' Trendline Residuals')

xlabel('Last '+aa+' Days')
```

```
ylabel('Residual (USD)')

pause

[n,m]=size(yy)

[n1,m1]=size(prdiff)

f=fit(yy',prdiff','fourier3'); %f will have the coeff of the fourier expansion

for i=1:a

yh(i)=trend(i)+f(i);

end

plot(yy,yh,'b')

hold

plot(yy,RV,'r')

title(name + ' Base Model')

xlabel('Last '+aa+' Days')

ylabel('Closing Price (USD)')

pause

prdiff2=(RV)-yh;

[n,m]=size(yh)

[n1,m1]=size(prdiff2)

%plot(yy,prdiff2)%

zz=linspace(1,300,300);

for x=1:300

prd(x)=p(1)*x+p(2)+f(x);
```

```
end

%plot(zz,prd)

plot(zz,prd+max(prdiff2),'g')

plot(zz,prd+min(prdiff2),'g')

plot(jj,fut,'b')

title(name + ' Future Prediction vs. Future Actual')

xlabel('Last '+aa+' Days and Beyond')

ylabel('Closing Price (USD)')

xline(a)

hold
```

Volatility-Driven Model:

```
load ('ICUI.csv')

prclose=ICUI(:,5);

aa="116";

name="ICU Medical (ICUI)";

a=116;

for i=1:502

    data(i)=prclose(503-i);

    historical(i)=prclose(i);

end

load ('ICUIfuture.csv')

prfuture=ICUIfuture(:,5);

for i=1:61

    fut(i)=prfuture(i);

end

sd=std(prclose)

jj=linspace(a+1,a+61,61);

xx=linspace(1,502,502);

plot(xx,historical)

title(name + ' Closing Prices')

xlabel('Days Since 11/5/2018')

ylabel('Closing Price (USD)')
```

```
pause

autocorr(data,501)

title(name + ' Autocorrelation')

xlabel('Lag')

ylabel('Autocorrelation')

pause

RV=prclose(503-a:502);

yy=linspace(1,a,a);

plot(yy,RV)

title(name + ' Relevant Period')

xlabel('Last '+aa+' Days')

ylabel('Closing Price (USD)')

hold

pause

p=polyfit(yy,transpose(RV),1)

for i=1:a

trend(i)=p(1)*i+p(2);

end

[n,m]=size(yy)

[n,m]=size(trend)

plot(yy,trend)

title(name + ' Closing Price /w Trendline')
```

```
xlabel('Last '+aa+' Days')

ylabel('Closing Price (USD)')

hold

pause

prdiff=transpose(RV)-trend;

plot(yy,prdiff)

title(name + ' Trendline Residuals')

xlabel('Last '+aa+' Days')

ylabel('Residual (USD)')

pause

f=fit(yy',prdiff','fourier3'); %f will have the coeff of the fourier expansion

for i=1:a

yh(i)=trend(i)+2.372419255*f(i);

end

plot(yy,yh,'b')

hold

plot(yy,RV,'r')

title(name + ' Base Model')

xlabel('Last '+aa+' Days')

ylabel('Closing Price (USD)')

pause

prdiff2=transpose(RV)-yh;
```

```
%plot(yy,prdiff2)%

zz=linspace(1,300,300);

for x=1:300

prd(x)=p(1)*x+p(2)+2.372419255*f(x);

end

%plot(zz,prd)

plot(zz,prd+max(prdiff2),'g')

plot(zz,prd+min(prdiff2),'g')

plot(jj,fut,'b')

title(name + ' Future Prediction vs. Future Actual')

xlabel('Last '+aa+' Days and Beyond')

ylabel('Closing Price (USD)')

xline(a)

hold
```